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Abstract

Smart grid is the key enabler of the main conceptual framework for Smart Home (SH) concept. The emergence of SH yields Home Energy Management Systems (HEMS) to enhance residential energy solutions. HEMS are capable of creating an automation network to provide many energy saving applications and customer comfort facilitation through Appliance Load Monitoring and Diagnosis (ALMD) technologies. ALMD enables load decomposition at the appliance level. An appliance-level analysis can benefit both customers and utilities by improving energy efficiency and subsequently reducing the electricity cost.

The ALMD system accounts for two main procedures of load identification and fault detection that lie at the root of this study. The former is offered by load monitoring phase. This phase can be executed by use of intrusive and non-intrusive methods. Nevertheless, due to different issues related to the first technique, the non-intrusive mechanism has been promoted. On the other side, the latter is realized through anomaly detection manners. These manners exploit the results of load monitoring step to detect any deviation in appliances' normal behavior. Consequently, the anomalous appliances are analyzed to be diagnosed in terms of either faulty or abnormal.

Accordingly, this essay commences with the first phase, in the context of Non-intrusive Load Monitoring (NILM). NILM entails essential prerequisites in order to realize a fruitful structure. These essentials generally vary based on customer's choice of appliances, their electrical characteristics, and environmental conditions. For example, in Quebec, Canada, where this study is conducted, the Electric Space Heaters (ESH) and Electric Water Heaters

(EWH) explain a significant share of household electricity consumption. As a worldwide uncommon case, this can bring about particular case studies of NILM. Therefore, the investigation into the prerequisite necessities that can notably affect the feasibility of a load recognition process through NILM techniques should be highly concerned. In accordance with this matter, an extensive discussion is provided that subsequently results in practical suggestions with regard to NILM's essential necessities. Furthermore, this analysis yields a semi-synthetic data generation approach that is proposed to assist with the demonstration of the importance of NILM's prerequisites. Particularly, the creation of this tool is motivated by the lack of appropriate data for Appliance Load Monitoring (ALM) studies in regions like Quebec. The statistical modeling methods and whole building energy simulators are employed to develop the data generation tool. The results demonstrate the capability of the developed tool to generate useful electricity consumption data for ALM researches.

According to NILM analytical process of load identification, many machine learning algorithms have been utilized. Generally, the choice of algorithms has been made based on important features related to targeted appliances and available information. However, the diagnosis capability is another element that should be considered in the method candidate due to the fact that the eventual ambition of an ALMD is not only load recognition. In addition, the chosen algorithms have mainly considered a time-invariant modeling structure that utilizes the static information of underlying databases to construct the models through exhaustive off-line training phases. These restrictions have motivated this research study to intend an appliance-level load modeling system in order to enable the diagnosis capacity of NILM. From this perspective, a framework is suggested that is capable of capturing the dynamic nature of power consumption by exploiting individual houses data. The suggested framework aims at a time-variant load modeling system by developing an adaptable on-line learning mechanism that is formulated in the context of an unsupervised machine learning method. Accordingly, this dissertation proposes the approach of adaptive on-line unsupervised household database construction of energy-intensive appliances to provide real-time appliance-level information and manipulate high-energy demands. This approach considers the specific case of Quebec by analyzing the data of EWH. The results demonstrate that the proposed data construction method is able to create and collect valid models of energy-expensive devices.

The diagnosis of anomalous appliances is another important application of household ALMD systems. Anomaly detection is an inevitable step towards decision making on the type of irregular electricity consumption. Nevertheless, this phase, particularly in the context of NILM has not been fairly taken into consideration. In fact, due to the tedious task of load disaggregation, the state-of-art NILM techniques are inadequate to enable effective anomaly detection services at the aggregate-level. Therefore, this argumentation recommends the idea of operation-time anomaly detection by providing an in-depth analysis of the nature of anomaly in household energy-intensive appliances as well as energy consumption behavior of a set of devices candidate. Such an extensive investigation assists with the development of efficient anomaly detection methods based on general electrical features of loads applicant. As a result, an on-line appliance-level anomaly detection system is proposed that is capable of continuously monitoring of energy consumption and providing in-operation information for diagnosis algorithms. This suggestion is further bolstered by improvements in cost-efficient smart plugs' technology. The results, obtained from actual experimentation on several case studies demonstrate that the proposed approach, performed by a set of straightforward techniques has a robust structure. Important remarks are elaborated within this study that can assist with future ambitions of aggregate-level anomaly detection.

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Contents

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List of Acronyms

Notation	Description
ADC	Appliance Database Constructor.
ALM	Appliance Load Monitoring.
ALMD	Appliance Load Monitoring and Diagnosis.
AMI	Advanced Metering Infrastructure.
ANILM	Advanced Non-Intrusive Load Monitoring.
ANN	Artificial Neural Network.
BEopt	Building Energy Optimization.
DA	Deferrable Appliances.
DL	Deep Learning.
DOR	Diagnostic Odds Ratio.
DR	Demand Response.
DSM	Demand-Side Management.
DT	Decision Tree.
DTA	Deferrable/Thermostatic Appliances.
ECO	Electricity Consumption and Occupancy.
EDHMM	Explicit-Duration Hidden Markov Models.
ESH	Electric Space Heaters.
EWH	Electric Water Heaters.
FHMM	Factorial Hidden Markov Models.

Notation	Description
FSM	Finite State Machine.
HEMS	Home Energy Management Systems.
HMM	Hidden Markov Models.
HSMM	Hidden Semi Markov Models.
IoT	Internet of Things.
ITCS	Intelligent Thermostatic Control Systems.
k-NN	k-Nearest Neighbor.
KDE	Kernel Density Estimation.
MES	Medium Energy Storage.
NILM	Non-Intrusive Load Monitoring.
PDF	Probability Density Function.
PEV	Plug-in Electric Vehicles.
PoI	Patterns of Interest.
REDD	Reference Energy Disaggregation Data Set.
REFIT	Personalised Retrofit Decision Support Tools For UK Homes Using Smart Home Technology.
SH	Smart Home.
SM	Smart Meters.
SVM	Support Vector Machine.
VA	Virtual Appliances.
VT	Viterbi Training.

Chapter 1 - Introduction

1.1 General context

Electricity is an essential secondary source to society for supplying energy demands. The households and companies' needs for electricity are increasing due to digitalization and electrification of the global economy. The steady growth in electricity demand causes its share in final energy consumption to rise from 19% today to 29% in 2050. On the demand side, worldwide consumers today spend $2.5 trillion on electricity, almost twice the amount in 2000. This accounts for 40% of their energy expenses, 8% more than it was in 2000, whilst oil stocks is portioned out less than 50% of their costs. On the supply side, global expenditure on electrical infrastructures in 2017 grew to $750 billion, more than accumulated funding on oil and gas industries, in which two-third of this investment belonged to renewables in the generation sector [1]. Likewise, in Quebec, Canada, where this study is conducted, electricity needs are projected to grow by 2026. Quebec people are among the largest consumers of electricity around the world. This is due to the huge amount of energy requirement for heating systems, specifically during severe winters as well as the low cost of electricity. Every time that the temperature falls by one degree in winter, the electricity use in Quebec rises by around 400 MW. Therefore, power shortages because of a substantial quantity of energy demand at peak periods is urgently concerned in Quebec. In fact, in this region, power usage is growing by 100 to 200 MW per year that can bring about a shortage of 1000 MW by 2025. Quebec's goal is to supply this demand through cheaper and more environmental solutions [2].

Accordingly, the provision of a reliable and secure supply of inexpensive electricity, while maintaining environmental ambitions is becoming the backbone of energy policy at the root of the 21st-century economy [1]. In order to obtain this arrangement, four principal manners can be intended: performing a more flexible power generation, performing a more flexible demand, utilizing energy storage, and enhancing the electricity grids. The latter can be enabled through the smart grid concept. The smart grid is the key enabler of the main conceptual framework for smart energy consumption in the future. In fact, the smart grid is an inevitable solution towards revolutionary electric power systems [1], [3].

Particularly, the expansion of smart grid technologies in demand-side sectors can assist with buildings' energy management as a decisive element of future electric grids. Buildings share the largest demand among all end-use sectors, as it can be seen in Figure 1-1. The residential sector in buildings has the highest share of electricity consumption. It should be noted that only appliances [1] consume more than 20% of overall global electricity demand today. Besides, in Canada, the sixth-largest electricity consumer with the highest per capita electricity demand of 15000 kWh around the world, buildings account for the highest share of electricity consumption, as shown in Figure 1-1. Residential sector shares %33 of Canada's electricity

[1]Appliances category includes large devices such as washing machines and small ones such as TV and excludes space heating, space cooling, water heating, and lighting.

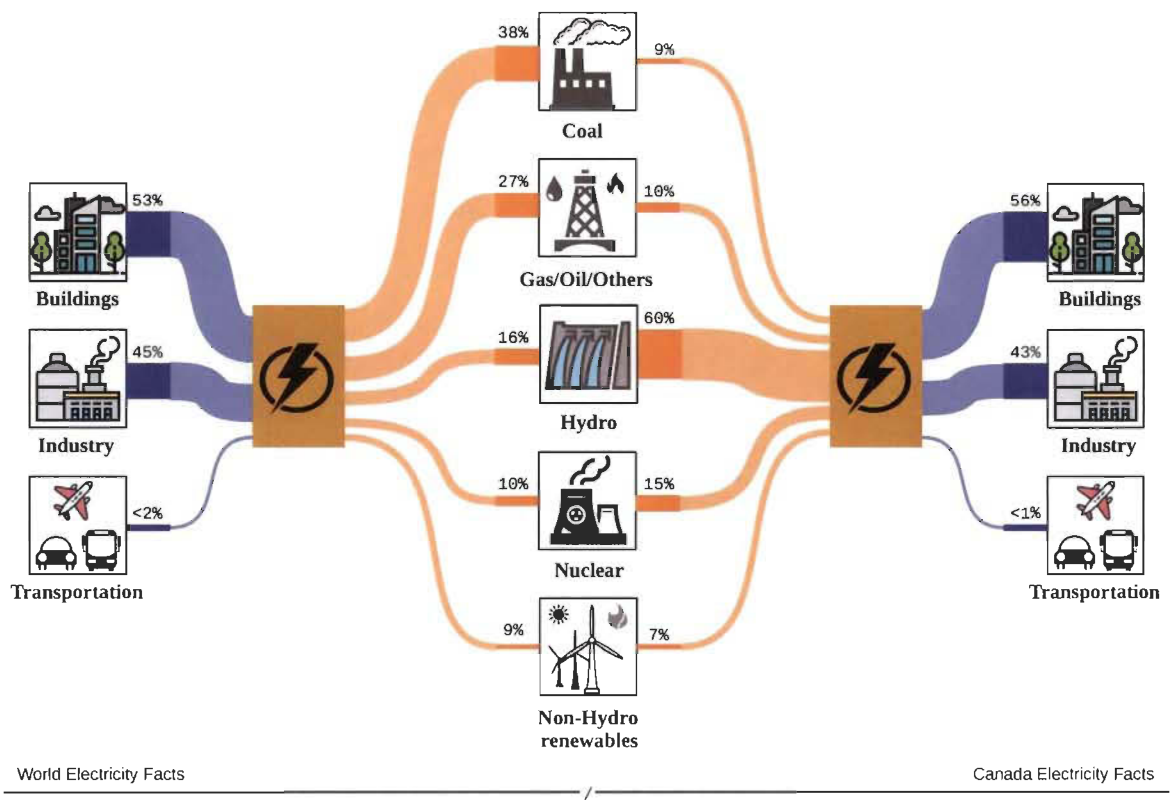


Figure 1-1 World and Canada electricity generation by main resources and consumption by main sectors [4], [5]

demand. In fact, buildings, particularly residential part, as an important driver of global electricity consumption increase, play a significant role in new energy policy scenarios [1], [6], [7]. Therefore, smart grid opportunities from one side and large electricity demand from the other side brings about a significant interest in deploying new energy research programs in the residential part. In this context, the research studies on load monitoring processes, especially in real-time, receive significant attention. By enabling load identification, these systems can facilitate energy-saving awareness and load diagnosis services that define the motivation of this essay, detailed in the following.

1.2 Motivation

The emergence of smart grid technologies in the residential sector enables the creation of Smart Home (SH). The SH concept promotes the Home Energy Management Systems (HEMS) by providing an automation network capable of substantially managing the flexibility of demand through enhanced Appliance Load Monitoring (ALM) [8], [9]. ALM can yield many energy-saving applications and customer comfort facilitation through the exploration of residential dynamic power usage [10], [11]. Real-time ALM can enable accurate tracking, effective evaluation, and augmented diagnosis of household energy consumption. The development of smart technologies in the context of residential ALM systems can result in an active load diagnosis and control of different household end-uses. It should be noted that the share of improved automation, monitoring, and control technologies in smart grid investments has grown to $33 billion in 2017 [1].

ALM is practiced in the context of intrusive and non-intrusive techniques. However, due to expensive sub-metering installations and difficult upgrade settings that impede the former and electrical and computer engineering technologies that promote the latter, the non-intrusive approach is favored [12], [13]. In fact, Non-Intrusive Load Monitoring (NILM) is acknowledged as an applicable approach to achieve the idea of residential smart energy usage by contributing advanced energy feedbacks. From this perspective, Smart Meters (SM) are a principal element in NILM realization and cost-effective opportunities recognition. Nevertheless, low-cost smart plug technologies are also favored due to their capability in offering direct load diagnosis and control of household energy-intensive appliances in terms of an intrusive approach [11]. Figure 1-2 illustrates the utilization of smart technologies to create an advanced ALM system for realizing the'smart readiness' of the household. In this framework, smart metering technologies are employed to perform ALM in order to provide appliance-level information that can be further used to manage energy-expensive loads [1], [14].

1.3 Appliance-level monitoring

The increase in end-users' monitoring and diagnosis capabilities of the variable loads, connected to the grid has resulted in load identification using ALM [15]. As mentioned, due to the challenges related to the intrusive approach of ALM, the non-intrusive one is promoted to

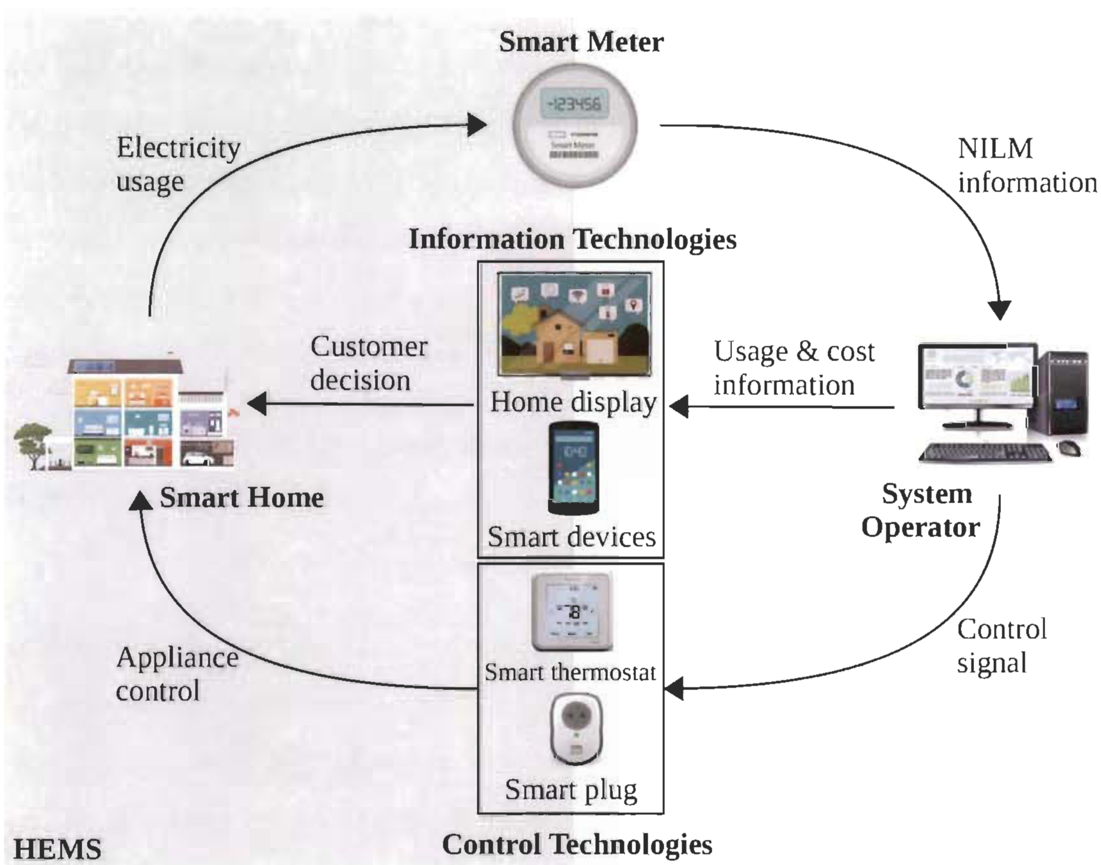


Figure 1-2 The realization of an enhanced ALM system by deploying different smart technologies [14].

identify the appliances' load. In fact, NILM facilitates the analysis of residential appliance-level information [8], [11]. From a technical viewpoint, NILM refers to any combination of physical hardware, metering equipment, and software with the explicit intention of being used to disaggregate the electrical load of a home from a single metering point. NILM can provide significant HEMS applications by using aggregated load data from smart meters [16], [17], expressed as below :

- Energy usage regulation: NILM can be utilized to apply innovative energy-saving solutions in households considering their significant share of total electricity consumption [18]. It can benefit customers not only by providing valuable energy feedback of individual appliances but also by enabling their participation in home energy management and power grid services [12], [19].

- Fault/abnormal usage detection: NILM can provide effective load diagnosis services. It can facilitate the diagnosis of excessive building energy consumption and help with component-level faulty operation detection [20]. NILM can be used for the recognition of potential health issues of electrical loads in the early stages. Generally, the diagnosis capacity of ALM can potentially save a major repair cost and minimize the operational downtime [21]–[23].

- Elderly surveillance and intrusion detection: NILM can present security services through remote monitoring and control of elderly surveillance as well as probable intrusion [22], [24].

- Novel electric bills: NILM can offer novel electric bills with beneficial information about appliances' energy usage and their consumption patterns since the bills nowadays are blind to detailed information on customers' electricity use. This can assist customers with acquiring proper knowledge about their energy consumption and thus effectively managing their usage behaviors [24].

Moreover, NILM can assist utilities to provide high-level Demand Response (DR) and flexible Demand-Side Management (DSM) programs [10], [27]. Particularly, household appliance-level information stimulates power system stakeholders to utilize the potential of deferrable loads (like Electric Space Heaters (ESH) and Electric Water Heaters (EWH)) monitoring in order to contribute to energy savings. For example, as stated by EU Energy Label regulation, temperature controls can boost the energy efficiency of a space heater up to %5 [1]. On the other side, EWH possess a notable capability in load control strategies and ancillary services that offer incentives to customers and dynamic power dispatch to utilities [28], [29]. The influence of deferrable appliances on energy-saving scenarios rises specifically in regions with cold climates like Canada due to their larger demand. The amount of electricity consumption that a household in Quebec allocates to ESH and EWH is around %14 more than a typical home, as depicted in Figure 1-3 [25], [26]. It is worth mentioning that NILM concept can be valuable for any situation without physical access to individual loads because of specific locations such as submarine positions or emergency conditions like high releasing radiation [22], [24]. Accordingly, NILM is acknowledged as an applicable load monitoring approach to achieve the notion of residential smart energy usage [11].

Generally, appliance-level feedback can result in a higher saving compared to aggregate feedback. This has been demonstrated in Figure 1-4 through providing the possible energy savings in household different electricity consumption levels. It can be observed that real-time

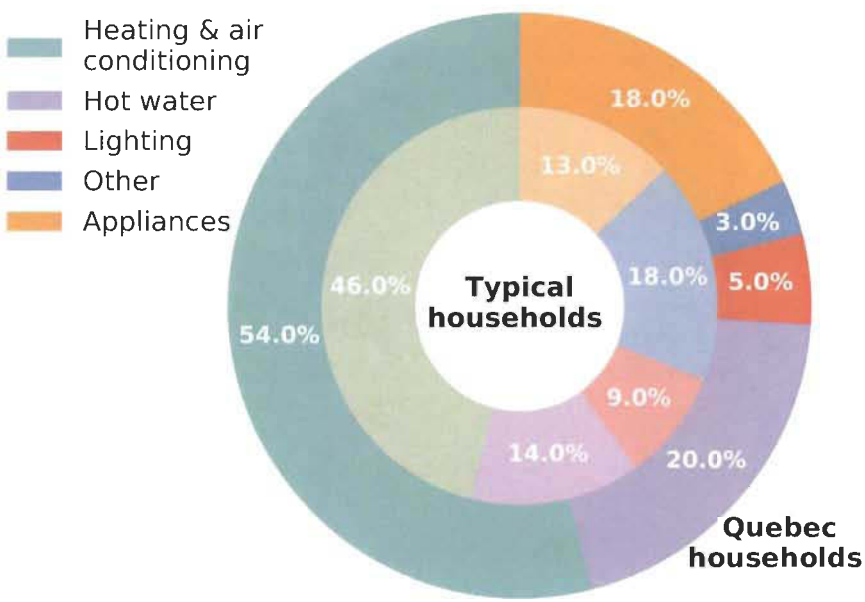


Figure 1-3 A comparison between the electricity consumption of the deferrable appliances in Quebec homes and typical homes, presented by different transparency of the same colors [25], [26].

appliance-level information, amplified with the personalized proposition (plus) can meet the highest savings [30]. Consequently, it can be comprehended that acquiring energy information at the most disaggregated level is the main ambition for any effective load monitoring system. Although NILM is the preferable method, this ambition gives importance to future low-cost smart plugs.

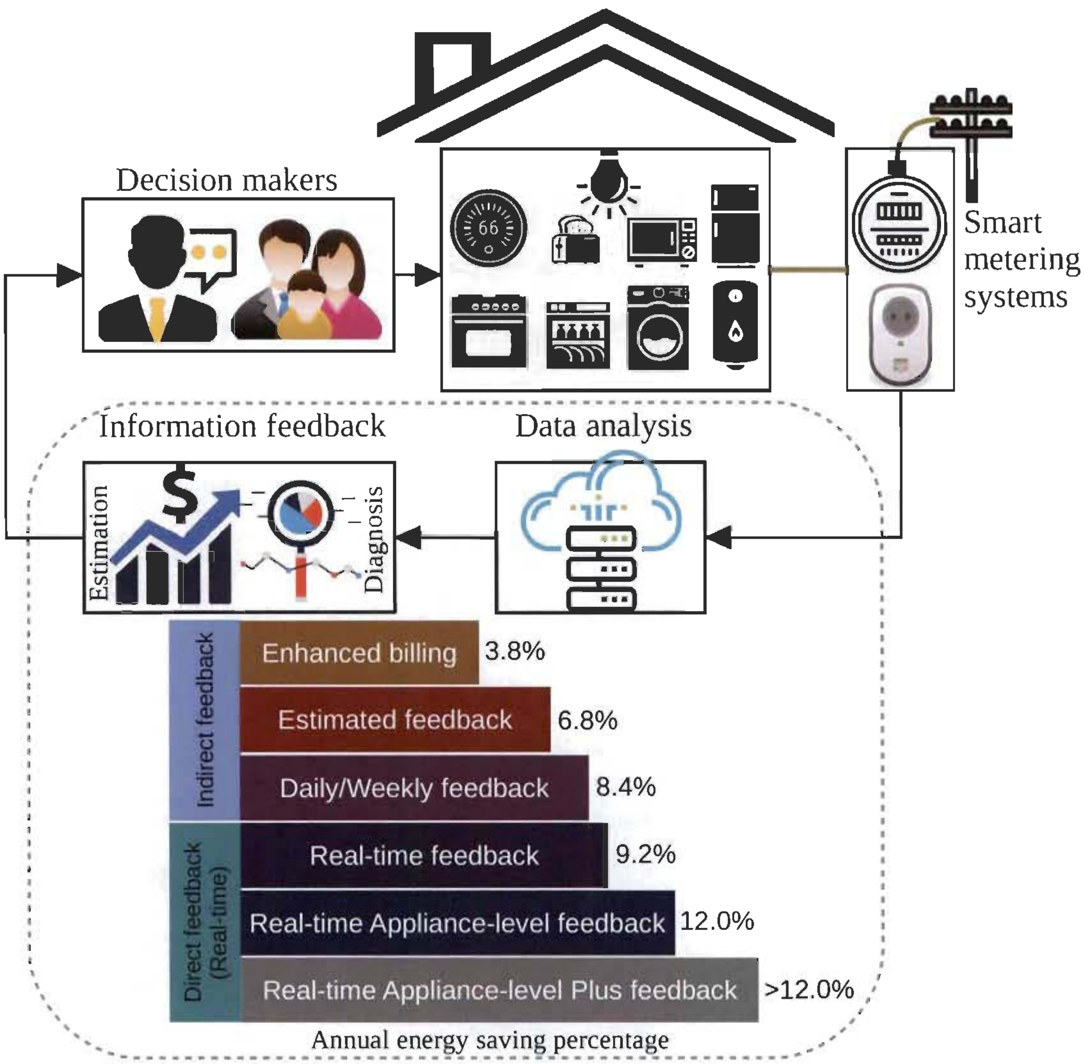


Figure 1-4 Annual energy saving potentials of household load monitoring in different consumption levels [30]

1.4 Problem statement

Regarding residential high electricity consumption, the first step in any improvement to energy solutions and potential savings is to understand how energy is utilized. Therefore, the examination of electrical energy usage is the fundamental matter of any ALM system, through which energy-saving awareness as the main ambition is targeted. This ambition is realized by two major services, accounting for quantification and diagnosis of electrical loads' energy consumption. The latter is primarily a procedure that exploits the information, provided by the former in the context of a load monitoring phase. Accordingly, the whole mechanism that offers the operation performance control (energy saving awareness) of household appliances can be explained in terms of an Appliance Load Monitoring and Diagnosis (ALMD) system.

In order to accomplish a fruitful ALMD, not only an effective load monitoring algorithm as the main focus of the literature is required but also a competent information space and a feasible anomaly detection method is desired [11], [31], [32]. With regard to the former, a flexible ALM system, specifically non-intrusive one, capable of capturing the dynamic of the power consumption in an on-line context is lacked. Although such a system is necessary to enable significant services of ALM such as diagnosis, it has been overlooked in the related studies. With regard to the latter, two significant matters need further attention. First, the provision of proficient data of energy-extensive loads in exceptional regions should be considered. In fact, the residential cases in these regions like Quebec can have significant potentials for energy improvements that signify ALM analysis. However, the publicly available data is not even limited but also related to common cases in the US and European countries. Second, an oriented load monitoring structure for practical anomaly detection and load diagnosis should be explored. Indeed, examining ALM systems capabilities for important applications such as anomaly detection is necessary after many years of developing a variety of monitoring methods. Nevertheless, the corresponding studies in both aggregate-level and appliance-level load monitoring have neglected to contribute related adequate research. The above concerns lie at the roots of the problematic of this study that targets the household energy-expensive appliances, particularly two-state loads. These issues are discussed in details below in terms of three essential elements of ALM.

1.4.1 The proficiency of database

An ALMD process is applied to a set of electrical and non-electrical information, extracted from their relevant data that is stored in a database. Therefore, the proficiency of a database is a critical prerequisite to achieve a successful ALMD since load monitoring algorithms require useful information to deliver appropriate results [33], [34]. A proficient database should comprise a real-world data that its characteristics account for all probable elements that influence the performance of energy estimation methods. However, collecting such a database is a costly, time-expensive, burdensome task due to the variety of household electrical appliances with different type/manufacture, which results in various electrical features and operational behaviors [35], [36]. The issue increases on the grounds that the choice of in-use devices is affected by the geographical properties that necessitates a measured database to be pertinent to individual regions. As demonstrated in Figure 1-3, in Quebec, ESH and EWH account for more than 70% of electricity consumption because of cold weather conditions. Not only these appliances are crucial for energy solutions but also they can bring about challenging load monitoring circumstances. Nevertheless, there are no publicly available databases to describe such a situation and majority of these databases neglect the measurements of the type of loads related to the exceptional geographical cases. It should be mentioned that geographical conditions can also define the necessity of non-electric information utilization to improve the energy-saving potentials. The above restrictions signify the idea of data generation that can be utilized for exceptional cases with diverse electricity consumption scenarios [10], [11]. Indeed, the proficiency of database is acknowledged through analyzing the adequacy of the information space as prerequisite necessity of an effective analytical process. Such an examination is another issue of developing useful ALMD systems that has been neglected in relevant studies.

1.4.2 The feasibility of ALM

The viability of a load monitoring framework is essentially concerned with NILM systems. Generally, NILM has been faced basic matters during many years of analysis that can be summarized as follow:

– Problem to track appliances with electronic control devices such as electrical heaters, which repeatedly execute very short ON cycles [37].

– Failure to discover appliances with continuously-variable power consumption that present an infinite number of states with a continuous range of operating power levels [22], [37]–[39].

– Inadequacy to distinguish low-power and continuously-variable appliances in the company of major loads [38]–[40].

– Challenges to recognize appliances within spatial or temporal overlapping conditions related to identical power usages or same time operations, respectively. [22], [24], [38], [41].

– Insufficiency to define appliances with similarity in electrical characteristics, which requires extracting more electrical signatures to disassociate them. [38], [39].

In Appendix A, this dissertation presents a study that demonstrates NILM significant issues related to the identification of household appliances with similar loads (the last item). It can be deduced that due to the NILM fundamental issues, an effective household load monitoring scenario should target the appliance-level analysis of loads with major power demands that their energy decomposition and estimation can intend notable energy savings and cost reductions [42]. The appeal for providing customers and utilities with feasible individual load information signifies the idea of appliance-level modeling. Appliance-level load modeling engages supervised and unsupervised methods, for which the former has been generally preferred due to the complexity of the latter [17], [23], [24]. Accordingly, in NILM, the efficient studies rely on a set of previously learned models of known appliances' load that are captured through an exhaustive training phase [19], [36], [43], [44]. In fact, they create time-invariant load models with fixed parameters by exploiting an off-line database with static information. These models provide an invariable examination of appliances' behavior over all the time and thus, are indifferent to changes in household total signal due to appliances characteristics' variation. Therefore, they are not sufficiently feasible to interpret the actual behavior of power consumption and enable diagnosis potentials. The following items add more insights into the aforementioned restrictions in details.

- Underlying databases: The off-line databases, used to extract the model parameters encompass a specific set of appliances' signatures of different features. Therefore, the elementary models can be either utilized for the same houses or generalized to the individual ones with similar appliances' characteristics [19], [44]. This aspect undergoes further issues related to the information proficiency of the exploited databases, described in the previous section. Nonetheless, a sufficient database, used to derive the load models can be still inadequate due to the lack of extensibility to consider newly manufactured appliances, presented in different houses.

- On-line operation: The on-line application of appliance-level modeling has been taken into consideration due to its necessity for the creation of an advanced NILM. Nevertheless, load disaggregators have mainly utilized an off-line training phase and the on-line aspect has been suggested for only an on-line disaggregation [31]. It is worth to mention that on-line application has been confused in some studies with the real-time concept due to the lack of a factual definition [43], [45]–[49]. Notwithstanding this confusion, real-time systems (one can read on-line) do not necessarily need to be fast [49], [50]. Actually, there is a wide-spread notion that these systems have to be executed in a short time. However, this strongly depends on their specific applications regarding targeted appliances, time intervals of energy feedback provision, and power grid stakeholders' (i.e. customers or utilities) priorities, which define the deadlines [50].

Indeed, utilizing an off-line training phase, constraining a flexible load disaggregation, and restricting load modeling scalability can decline NILM capability to capture the dynamic behavior of the energy consumption. Subsequently, this can bring about further issues related to aggregated-level load diagnosis potentials [51].

1.4.3 The diagnosis of anomalous appliances

ALM can ease the inspection of individual appliances' behavior in total energy demand, particularly their faulty/abnormal usage. Indeed, household electrical appliances can face operational conditions that jeopardize their normal operation and define them as anomalous [52], [53]. Appliances' anomaly detection is stimulated from the perspective of both customers to reduce the energy costs and utility to enable energy efficiency improvements [54], [55]. Effective anomaly detection seeks a framework capable of continuous monitoring of appliances' consumption (at the most disaggregated level) in order to capture their dynamic behavior for the diagnosis algorithm's applications. Such a mechanism can be targeted by means of ALMD systems in the context of both intrusive and non-intrusive [31], [56]. Although, the monitoring aspects of these systems have been intensely investigated, their diagnosis capability has not been decently taken into consideration. Considering NILM, only the proficiency of load disaggregation methods for diagnosis services have been noticed in a few studies [32], [57]. In fact, due to the tedious practice of load disaggregation, it has been the focal point of NILM researches. Nonetheless, state-of-the-art NILM methods are not adequate to provide efficient load diagnosis services [31], [57]. The dynamic stochastic nature of anomaly in electrical appliances, an expensive complication due to the wide range of appliances with different operating features, and the limited instances of loads' anomalous data can be acknowledged as the main reasons that undermine the diagnosis capacity of NILM [36], [52]. Therefore, an appliance-level anomaly detection approach is signified that examines a targeted-appliance in-depth and subsequently suggests an efficient diagnosis method. This concept is advertised by the inadequacy of aggregate-level anomaly detection methods and improvements in cost-efficient smart plugs technology [58].

1.5 Objectives and contributions

Our main purpose is to address the drawbacks that have been described within three essential elements in the previous section. In fact, the investigation into ALMD systems based on these aspects has led to an ameliorated understating of their actual opportunities and challenges. The novelty of this study is to propose applicable approaches with regard to these components, which their relevant issues can hinder a practical utilization. These approaches are described through the following specific objectives. Generally, the essence of our suggestions targets an on-line appliance-level load monitoring and anomaly detection of household energy-expensive loads.

1. An investigation is aimed to define the essential prerequisite of ALM systems in order to uncover their key requirements for a prosperous implementation with regard to energy-intensive devices. Furthermore, a mechanism is intended to demonstrate the complication of energy-expensive appliances' load monitoring in exceptional cases specifically, Canadian households. Consequently, the development of a semi-synthetic data generation tool is proposed to address these intentions.

2. With a focus on energy-demanding devices, an autonomous appliance-level load modeling framework is designated. By means of this structure, a flexible process capable of appliances' model management, in-operation information provision, and energy quantization is purposed. In fact, intending a NILM with diagnosis ability is the main motivation for developing such an architecture. As a result, an adaptive on-line database construction approach is proposed to realize the targeted procedure.

3. A thorough analysis is focused to examine ALM potentials for anomaly detection in aggregate and appliance levels. Accordingly, an appliance-level anomaly detection procedure is intended to effectively capture any operation deviation from normality. As a consequence of an in-depth examination, an on-line operation-time anomaly detection approach is proposed to efficiently utilize ALM for load diagnosis purposes.

Due to their significance for energy solutions, household energy-intensive appliances are the focal point of this study. Furthermore, this work attempts to utilize straightforward algorithms with regard to actual implementation. The essence of the provided analyses mainly signifies the unsupervised machine learning methods albeit their complexity. As a result, the following contributions in accordance with the specified concerns and intended goals are proposed.

- Data generation approach: Due to the lack of information about exceptional appliances, specifically Canadian energy-expensive loads, a simulation framework for household energy consumption analysis is established that contributes: i) A database development tool capable of generating synthetic data of Quebec energy-intensive appliances, accounting for ESH and EWH; ii) A structure capable of creating appealing time-extended load monitoring and control scenarios by using random schedules of appliances operation, which can be conditioned by non-electric information like outside temperature.

- Household database contraction approach: Due to the time-varying behavior of household power consumption, an autonomous household database construction approach is proposed in terms of: i) a flexible load modeling framework that is designed by a set of straightforward algorithms with no prior information; ii) a recurrent pattern recognition process that is able to detect and maintain probable load models; iii) an adaptable procedure that is capable of realizing an on-line load model learning mechanism; iv) a load model construction of major appliances that their parameters are directly extracted from the aggregated signal.

- On-line anomaly detection approach: Through a comprehensive study on the concept of anomaly in households, a full appliance-specific load monitoring and anomaly detection approach is suggested that presents: i) an on-line operation-time anomaly detection system with generalization ability that is dynamic to capture any deviation from normality in terms of faulty and abnormal operations; ii) a robust structure that is performed by reliable electrical information and requires minimum intrusion, least amount of information, and low-resolution data (highly compatible with current metering technologies); iii) an efficient modeling process of the normal behavior of appliances candidate that is developed with application to operation-time anomaly detection

After 30 years of investigation into mainly one aspect of ALM systems, particularly load disaggregation in the context NILM, the innovation of this study is to tackle other aspects of such systems due to their multi-facet nature. Such an intention has resulted in extensive investigations with the aim of an operative ALM that also targets the recognition of abnormality through employing the routine power consumption information. Furthermore, this aim has necessitated the development of different procedures that require their specific accuracy metrics for a careful evaluation. As a result, a thorough analysis with regard to each objective has been developed.

1.6 Methodology

The methodology of this dissertation is outlined in three common phases regarding Figure 1-5. Firstly, a comprehensive review is conducted to characterize the opportunities and challenges of ALMD studies in the literature. This examination aids in specifying the objectives and their necessities. Secondly, state-of-the-art methods are explored in order to define useful mechanisms with regard to the prescribed goals. These mechanisms are defined by investigating the existing algorithms and tools whose properties can present a good opportunity for effective and feasible propositions. Consequently, relevant approaches are proposed and their requirements are satisfied. Thirdly, analytical simulation and actual experimentation are employed to examine the suggested manners by use of real-world data of either public databases or laboratory measurements. For this matter, an experimental house with a functional acquisition system has been constructed to supply the actual data related to different experimental tests. Subsequently, the performance, simplicity, applicability, and limitation of every proposition are thoroughly analyzed and compared with the relevant researches. Indeed, for the examination of each ALMD study, a rigorous evaluation process is exploited. In the following, the methodology steps are detailed in accordance with each proposition, described in the previous section.

- Data generation approach: In order to develop a useful tool for simulating real-world scenarios, important features of publicly available databases are probed. Accordingly, by means of statistical analysis, the actual data of household appliances from a well-known database are explored in order to model their consumption schedules. In addition, whole-building simulators are investigated to identify an appropriate simulation structure for generating the synthetic data of targeted loads (in our case ESH and EWH). Afterward, a post-processing method is studied to modulate the artificial data of these loads and create their ON/OFF load profiles.

- Household database contraction approach: As the fundamental of appliance load modeling in aggregate level, household load disaggregation mechanisms are extensively analyzed. Particularly, probabilistic methods are examined due to their capability to provide a sensible interpretation of appliances' physical behavior. This examination focuses on the manners that are good fit for on-line unsupervised learning of finite-state load models. Additionally, clustering algorithms are studied in order to find effective techniques for classifying appliances operation. Specifically, non-parametric statistical means of clustering are evaluated because of their competence in unsupervised frameworks. Moreover, adaptive procedures are assessed to find out their ability to manage recurrent patterns and models upgrade of the loads. Different accuracy metrics are analyzed in order to define a set of efficient ones for a careful examination of both pattern recognition and model construction phases, necessitated by the proposed approach.

- On-line anomaly detection approach: A thorough research is focused on the means of household appliances' anomaly detection in both aggregate and appliance levels. An overview is carried out to determine the anomaly nature of household electrical devices, the anomalous behavior of major ones (whom have a finite-state load), and their readily available electrical features for actual experimentation. Consequently, a set of appliances candidate, located in an experimental house in our lab are chosen for a practical study. For these devices, different anomaly scenarios are exercised to analyze

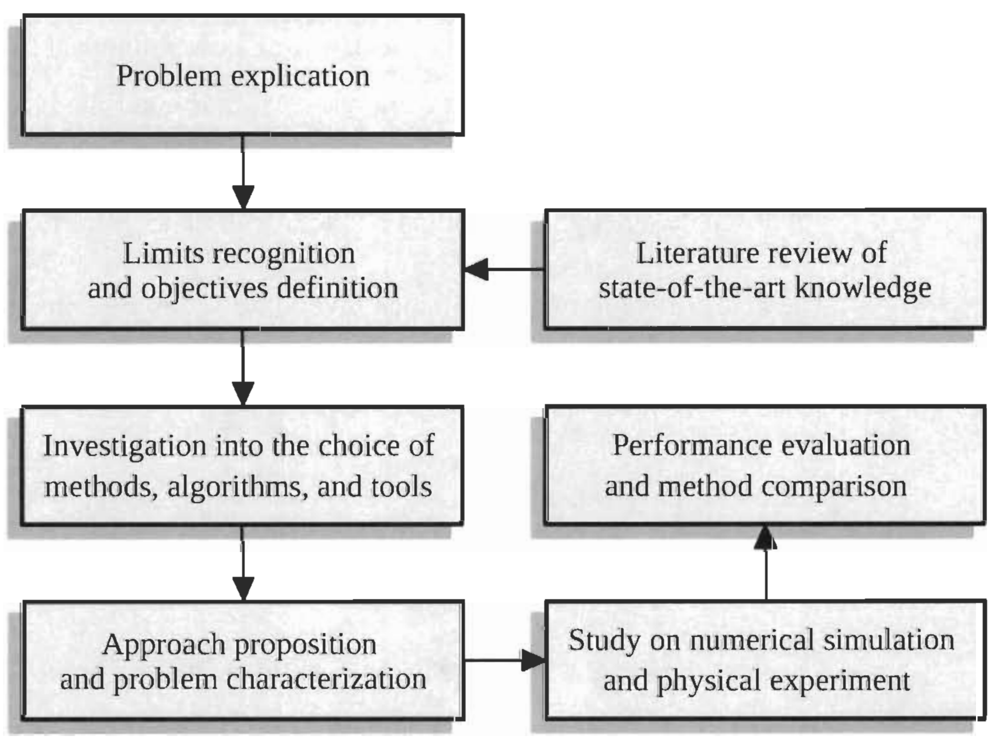


Figure 1-5 The research methodology

their behavior via continuous monitoring. Furthermore, machine-learning methods are studied to define practical techniques that are suitable for real implementation. This analysis aims straightforward algorithms for normal behavior modeling and anomalous operation detection. Subsequently, several diagnostic tests are considered to evaluate the performance of the anomaly detection mechanism.

1.6.1 Research hypothesis

With regard to the proposed approaches and utilized methods of this research, the following hypotheses are considered for both load monitoring and anomaly detection analyses.

- Regarding smart metering capabilities, methods that enable a low-frequency steady-state analysis are considered. A sampling rate is desired that can provide a sufficient edge detection of appliances' operation changes.
- Targeted appliances are finite-state periodic/regular loads such as refrigerator/stove with high power demands that can notably affect household energy consumption and thus; crucial to both customers and utility.
- The low power/irregular devices such as low-power compact fluorescent/iron and continuously variable appliances like power electronic controlled loads are not in the scope of the investigation. Actually, most of ALMD have ignored these loads since they are not normally among household appliances with major power consumption.
- The analyzing aggregate/appliance-level time series are considered to carry out a stationary process.

1.7 Manuscript organization

The rest of this document is organized as follows.

- Chapter 2 provides a literature review of state-of-the-art approaches to ALMD. In fact, this manuscript is written based on the articles. Each article comprises an in-depth study into the prior art, principally corresponding to its subject. Accordingly, the articles offer an extensive background that covers all the matters, targeted by this document. Therefore, in this chapter, a general description of the multi-facet nature of ALM is provided that is further followed by specific explanations in each article.

- Chapter 3 presents the articles that have been dedicated to each objective. It consists of three papers for each of which, a complete study that targets an important problematic, a set of contributions, a numerical/experimental analysis, and an eventual discussion are devoted. The first work is an exhaustive study for which, its algorithmic aspects are supported by supplementary research. This research develops the idea of data generation tool. The second manuscript details the approach of adaptive on-line household database construction. The third paper presents the suggested on-line operation-time anomaly detection system. It should be noted that each article is preceded with a brief description that outlines its content.

- Chapter 4 prepares an in-depth discussion on the ALMD concept as a consequence of the analyses, provided in the previous section. Through this discussion, new opportunities and challenges that can be investigated in terms of further research subjects are emphasized. From a realistic viewpoint, this section aims to elaborate remarks on essential elements of a usable ALMD that have their roots in related discussions, laid out throughout each article.

- Chapter 5 concludes this thesis. Considering the key objectives, this document has attempted to develop an exhaustive analysis to fulfill its ambitions within several studies. The novelty of these researches is their proposition to other aspects of ALM that are not only feasible but also interesting considering many years of mainly focusing on the fundamental challenges of ALM in the context of NILM

Chapter 2 - State-of-the-art

2.1 Introduction to ALM

Household ALM is the key platform to acquire appliances' information that is supplied to customers and utilities for their specific energy-saving matters. Particularly, the acquired knowledge can enable the diagnosis of anomalous appliances by providing the essentials for diagnostic estimation algorithms. In fact, the recent interest in enabling the diagnosis ability of ALM systems has necessitated a further examination of its anomaly detection requirements in both intrusive and non-intrusive aspects [31], [57]. Accordingly, this section provides an investigation into important features of load monitoring and anomaly detection as the essential elements of ALMD. Specifically, the literature focuses on NILM system by exploring its different procedures and their characteristics. Furthermore, the basis of anomaly in household electrical appliances is examined from different perspectives. Since this document is presented by manuscripts for each a detailed prior art has been contributed, this section provides a general description of important ALMD principals [10], [11], [31], [42].

Due to installation ease, overall monitoring capability, and efficient costs, NILM approach is promoted to facilitate a flexible foundation for obtaining appliances' in-operation information. NILM realizes a perfect structure for the identification of targeted devices through the ability to relate the monitored electrical waveforms to individual appliances operation [31], [59]. NILM concept proposed by Hart [60] in 1992, is the practice of disaggregating household total electrical load measured at a single point into individual appliances signal, using the combination of an electrical acquisition system and signal processing algorithms [11], [17], [60]. From ALM standpoint, NILM technology has been studying for a long time, however, it requires more progression in terms of employed load disaggregation algorithms as well as required essential prerequisites to be regarded as a solved problem [61]. Figure 2-1

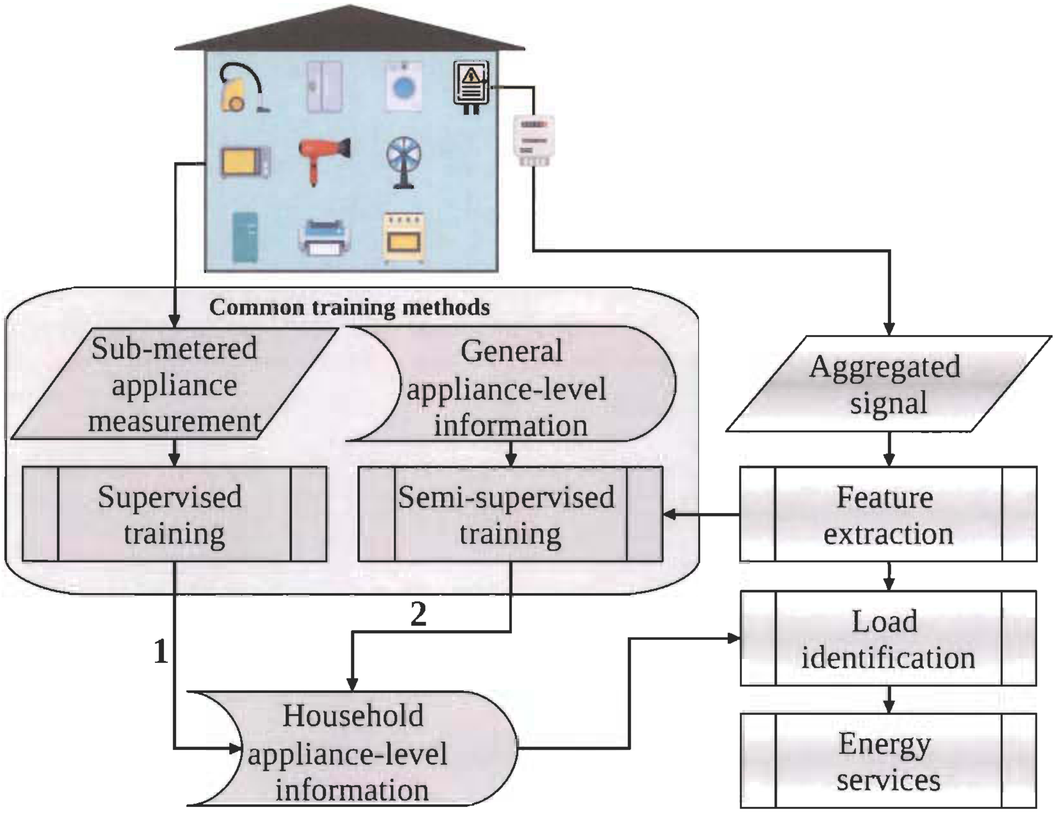
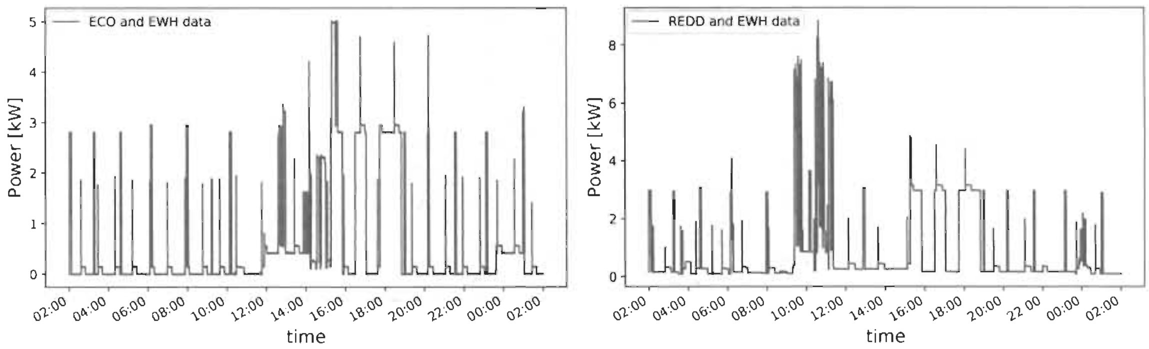


Figure 2-1 NILM procedure of load identification and energy services' provision

shows NILM structure by describing the load identification process and its common learning mechanisms. These mechanisms are discussed in details below. Furthermore, Figure 2-2 exemplifies the aggregated power profiles of two typical houses from ECO [17] and REDD [62] as common publicly available databases that are combined with an EWH load profile regarding the Quebec case.

2.2 Feature extraction

In this step, the electrical characteristics, considered for the NILM analysis are execrated from the aggregated signal. These properties can be generally classified into three categories as follows.



(a) (b)

Figure 2-2 Aggregated power profiles of (a) ECO house number 2 and (b) REDD house number 1 combined with an EWH profile

2.2.1 *Steady-state features*

The primary approach to feature extraction utilizes steady-state properties that are derived from stable electrical conditions of appliances' operating states [22]. This method principally detects either power levels or changes of an appliance's operation states in the context of a power-based analysis. In addition, this category accounts for waveform-based techniques that exploit the current and voltage trajectories of appliances in terms of V-I curves [40]. The steady-state based approaches are more feasible from the perspective of smart meters since they measure and transmit active power at relatively low sampling rate i.e. 1 Hz [37], [63], [64]. Furthermore, they are a more suitable choice from the viewpoint of customers. The additive ability of steady-state signatures allows simultaneous events to be properly analyzed [22]. These signatures are much easier to detect that support cost-effective ALM methods [22], [65]. On the other hand, the steady-state power changes can be influenced by temperature rise during the appliance's operation [65], [66]. In addition, this approach can face challenges related to both spatial and time overlapping of particularly, appliances with low-power usage [40], [66], [67].

2.2.2 *Transient features*

These features are derived from transition states of appliances' operation. The parameters that explain transients are their size, duration, and time [22], [65], [67]. Transient characteristics can provide useful information that assists with a steady-state analysis. For example, appliances having similar steady-state signatures can have very different transient turn-on information [22], [65]. Furthermore, they undergo less overlapping conditions [38], [40], [66]. The transients information can be considered as supplementary knowledge in the lack of other general properties such as reactive power [66].

2.2.3 Harmonic features

Harmonics are usually employed as additional features to active and reactive power consumption information [40]. In fact, a spectral envelope analysis can aid in identifying appliances that can not be detected by their macroscopic features [40], [68], [69]. Harmonics can be explored by using both steady-state and transient signals. They can aid in the identification of non-linear loads with non-sinusoidal current waveform [66]. Although harmonic-based methods can benefit appliances' operation detection, they experience difficulties in measuring energy consumption as an essential goal of NILM systems. They can require excessive training and face robustness issues in the presence of new loads [66], [70]. Furthermore, these features can be influenced by electromagnetic interference and electrical wiring [66].

Indeed, the choice of electrical characteristics for the feature extraction phase is notably affected by database proficiency, mainly appliances candidate and sampling frequency of data [11]. Therefore, in the first step, an explicit choice has to be carried out on targeted appliances. This has resulted in different load classifications, represented in numerous researches based on their technical notions of proposed NILM analysis [71], [72]. Normally, appliances are classified according to the number of their steady-state operations. Figure 2-3 explains household appliances classification based on their operation states.

Consequently, appliances decision can facilitate a suitable choice of sampling frequency with regard to the construction of an efficient database. As mentioned, the feasibility of NILM analytical process depends on the quality and sufficiency of some crucial factors that should be met by properties of the utilized database [11]. These factors should be defined based on NILM's targeted applications that are regulated in accordance with customer preferences and system operator interests. Indeed, specifying the implementations can assist with appliances candidate and techniques decision that in turn, enhances the NILM practice [11], [40], [73]. It

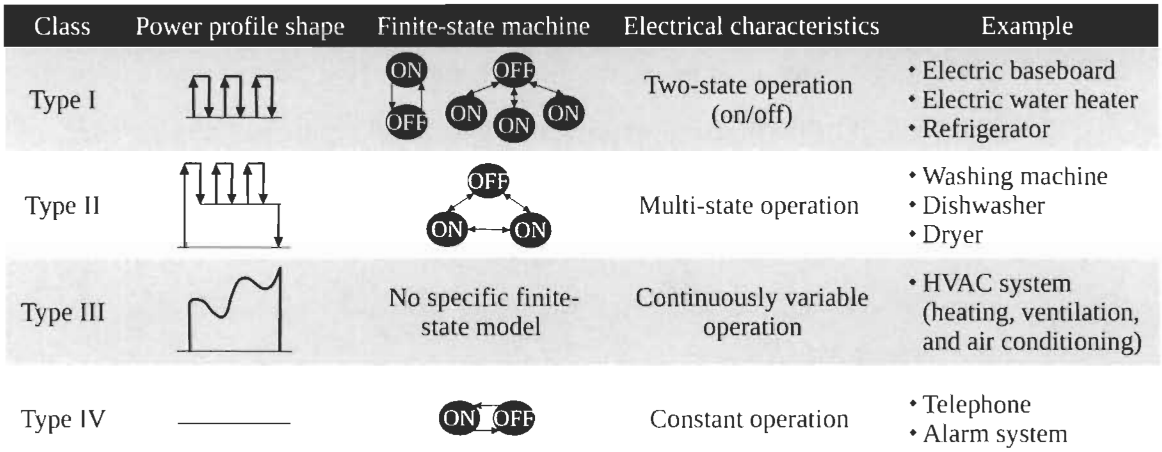


Figure 2-3 Household appliances' classification based on active power operation states

is noted that energy saving as the foundation of NILM is the mutual concern of both customers and system operator and thus; the common application of NILM systems [30]. Table 2-1 presents the impacts of the targeted set of household loads on the choice of preferred feature space and sampling frequency in a general aspect [30], [40], [61].

TABLE 2-1 The information space of NILM practices, employed in the literature

Household appliances	Sampling granularity	Electrical features	Appliance candidate
Major loads	1 h - 15 min	P & Q	heating/cooling systems
	1 min - 1 sec	P & Q	refrigerator, electric baseboards
Small loads	1.2 - 2 kHz	V & I waveforms	toaster, microwave oven
Electronic loads	2 - 40 kHz	V & I waveforms	TV, computer
Household power tools	$\geq$ 10 MHz	Current transient	drill

2.3 Load identification

The NILM procedure is to disaggregate the total electrical signal in order to identify the existing individual loads and consequently, examine their energy consumption. In fact, household energy-intensive appliances are finite-state loads that can be treated as a combination of two-state devices. Therefore, the Finite State Machine (FSM) of a multi-state load l, resulting from its two-state sub-profiles can be expressed by (2-1):

$$y_k^l = \mathbf{z}_k \mathbf{u} + \mathrm{e}_k \tag{2-1}$$

where at discrete time k, $\mathbf{z}_k$ is the row vector of the binary representation of operation states, i.e. zero for OFF and one for ON state, $\mathbf{u}$ is the column vector of sub-profiles power consumption, and e_k is the noise, which can be attributed to different sources such as measurement system and the environment. Accordingly, the aggregated power at k including L finite-state appliances can be described by (2-2):

$$y_k = \sum_{l=1}^{L} y_k^l + r_k + e_k \tag{2-2}$$

that r_k is the consumption of non-finite-state loads as residual and e_k is the noise. NILM methods are provided to optimally infer individual appliances operation by using different kind of observations of electrical features and prior knowledge as well.

From the standpoint of different approaches to analytical procedures and mathematical algorithms, NILM has been broadly reported in the literature. Zeifman and Roth [61] studied NILM with the focus of interest in signature examination for feature extraction as the first step of NILM general process. Tabatabaei et al. [74] probed NILM mainly by concentrating on computational algorithms consisting of machine learning techniques for load disaggregation and classification as the second step of NILM common practice. Zoha et al. [40] reviewed NILM whole process by presenting the same viewpoint as [61] regarding feature extraction step and moreover, discussing mathematical developments of load disaggregation phase.

As a matter of fact, NILM approaches based on low-rate steady-state load disaggregation methods are promoted due to the tendency in designing smart meters that are able to provide low-sampling rate data regarding their real-world deployment issues [30]. Appropriately, state-based approaches are used to effectively explain the aggregated signal as the combination of state-changes of individual appliances' sequence. Subsequently, machine learning algorithms specifically, Hidden Markov Models (HMM) are favored due to their capability to provide analytical state-based models of household appliances [40], [61], [75]. Henao [76] carried out a thorough study on the capability of variants of HMM to describe the total signal, particularly in the context of Quebec households with challenging loads of ESH and EWH. In fact, due to actual appliances behavior, probabilistic methods such as HMM have been preferred to deterministic manners like Support Vector Machine (SVM) [77] and heuristic techniques like Genetic Algorithms (GA) [78]. Artificial Neural Network (ANN) [79] and k-Nearest

Neighbor (k-NN) [80] have been other methods, used for load disaggregation. ANN is not complicated to utilize but at the cost of arbitrary training, possible local maxima convergence, and overfitting. In addition, k-NN as a clustering method that uses distance functions can be slow and memory expensive in the presence of large number of data. Most recently, load disaggregation algorithms, developed by exploiting variants of Markov models in terms of supervised and unsupervised approaches have received significant attention [19], [43], [44], [75]. In fact, these approaches reflect learning mechanisms that have been utilized for appliances' model construction, discussed in what follows.

2.4 Appliance-level model learning approaches

Appliance-level modeling process requires useful information that is supplied by a feature space, extracted from raw data. Consequently, these information are utilized to build models and recognize appliances [12], [47], [81]–[85]. Machine learning, widely used for power system applications has been the main learning method for NILM. In order to become more distinct in the choice of machine learning techniques, it is essential to notice the following machine learning notions [36], [86].

- Supervised learning: this aspect utilizes priors/labeled data to build a model.
- Unsupervised learning: this concept uses no priors/labeled data to construct a model.
- Semi-supervised learning: this notion exploits a small amount of labeled data with a large amount of unlabeled data to create a model.

With regard to machine learning applications for appliance-level load modeling, the main NILM approaches can be defined.

2.4.1 Supervised NILM

This idea uses sub-metered appliance data to build a model for load disaggregation. The majority of NILM studies are based on this approach that employs a training phase. During this phase, the models of known appliances are learned and subsequently, used to identify their corresponding loads in the aggregated signal through disaggregation. The learning process can use either sub-metered data of individual appliances [87] or aggregated power signal [64]. In the latter, for learning a specific appliance's signature, the algorithm needs to find a period of time in the aggregated signal, during which only the targeted appliance is operating. Consequently, the efficiency of supervised techniques declines in the presence of unknown appliances' load in the aggregated signal. Supervised NILM methods are mainly off-line processes in which, load disaggregation problem is analyzed through two separate phases of models' learning and loads' recognition. ANN, SVM, and k-NN can be referred to as popular NILM supervised techniques.

2.4.2 Unsupervised NILM

Although this approach avoids using sub-metered data and maintains the reduction of space of information towards an unsupervised solution, it commonly utilizes general appliances information and actively adjusts them to specific household appliances. This means that unsupervised NILM can be interpreted as a semi-supervised machine learning problem. The variants of HMM, combined with clustering techniques are common NILM unsupervised manners. Unsupervised methods signify a real-time concept since they intend no/less training process. Generally, the critical issue with training phase of any method is the short training periods that are not sufficient for appliance recognition practice. To be precise, the training procedures specifically based on the aggregated signal should take into account the following notes [74].

- Frequent regular appliances such as refrigerator and freezer are simple to find due to a routine periodic operation.
- Frequent irregular appliances such as TV, stove, and EWH that have short operation can bring about a difficult learning phase specifically, with the occurrence of overlapping conditions.
- Infrequent appliances such as washing machines can face challenges with locating an isolated period for their train.

It should be noted that the aforementioned techniques describe common learning concepts. There are studies that have intended a completely unsupervised structure on the basis of an unsupervised machine learning method [31], [60], [88]. Unsupervised NILM is literally challenging due to different reasons, for example inadequate sampling intervals that can cause feature lost and identical power signatures that can avoid correct appliance identification. Accordingly, any efficient NILM practice requires a level of prior knowledge. General information can be either the number of states of a multi-state appliance e.g. a dryer, variations in power demand of a domestic usage e.g. an electric water heater, or operation time of a household load e.g. a refrigerator.

2.4.3 Real-time concept

In addition, the term real-time is another aspect, concerned by NILM studies. It is a widespread myth that real-time systems have to be fast [12], [43], [45], [47]–[49], [89] however, by definition, they have to be fast enough to guarantee the required deadlines for processing an application [50]. Therefore, in the context of real-time, a late result even correct is interpreted as wrong [50]. The term ‘late’ has to be defined according to the specific applications. As a matter of fact, the deadline is the only parameter that expresses the primary difference between real-time and non-real-time concepts [50]. This highlights the importance of application definition in order to clarify the deadline of a real-time system. Generally, in ALM systems, applications can be decided in different contexts related to energy estimation and load diagnosis feedback. Furthermore, these contexts should be handled based on the operational behavior of appliances candidate. Moreover, the real-time aspect does not necessarily consider either an on or off line system [47], [48]. It is probable that a real-time system accounts for static calculations with cyclic occurrence. Therefore, a real-time framework can consist of off-line processes that are executed while no run-time parameters are proceeded [50]. Accordingly, Figure 2-4 illustrates the general structure of NILM different learning procedures. The framework of a real-time unsupervised NILM includes off-line labeling. It is noted that the labeling is not considered in on-line procedure since one of the characteristics of an on-line system is to function without human intervention.

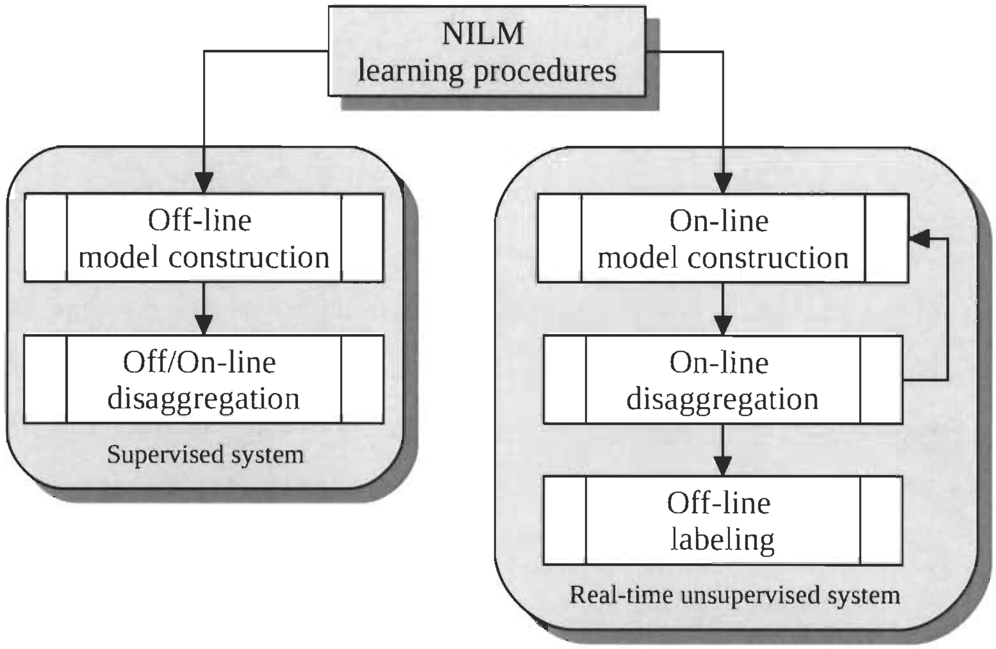


Figure 2-4 General structure of NILM training processes

2.5 Anomaly detection

Anomaly detection plays a key role in load monitoring and predictive maintenance [90]. Generally, an anomaly detection method is determined based on the nature of anomaly, which is categorized into three different classes. The simplest type, known as 'point anomaly', is a single data instance that is anomalous due to a large deviation from the rest of the data. The second class, expressed as 'contextual anomaly', refers to a deviation in a particular context regarding the structure of the data. For example, unless it is winter, a record of -30°C can be anomalous. The third category, defined as 'collective anomaly', implies a data portion that is collectively, not necessarily individually, anomalous [52]. The concept of anomaly detection has been broadly explored in different research domains such as computer networks, image recognition, and machine operation [91]–[95]. In the context of power systems, this concept has been generally studied in the main grid sectors [59], [96]–[98].

In the residential zone, electrical appliances can undergo operational conditions that violate their normal operation. These abnormal conditions can be attributed to different causes that identify an appliance as anomalous. The consumption pattern of an anomalous appliance deviates from its expected behavior that complies with normality [52], [53]. Likewise, machine-learning techniques have been widely utilized to formulate an anomaly detection problem [99], [100]. From this standpoint, the same mechanisms can be defined that account for: 'Supervised', that is training a classifier by using labeled classes of both normal and anomalous data instances; 'Semi-supervised', that is training only by utilizing a labeled set of normal data; and 'Unsupervised', that requires no training set since it groups the data under several clusters and defines dissimilar samples as anomaly. It should be noted that the supervised techniques simply consider an anomaly detection as a classification problem. On the other side, the semi-supervised methods are broadly exploited to separate outliers regarding normal samples (especially, when the classes are imbalance) [53].

The intention of the above discussion has been to provide a general comprehension of ALMD systems that is followed by a detailed investigation into the literature, presented by every article.

Chapter 3 - Article-based statement of the results

3.1 Introduction

The examination of the intended objectives is presented within the articles in this section. Notwithstanding the previous discussions, every article details the contribution, the approach, and the prior art regarding the proposed objective. Accordingly, the mathematical methods and experimental procedures to achieve the ambitions are described. Subsequently, the evaluations and results are reported to demonstrate the efficiency of the developed frameworks in every manuscript. The following sections offer the articles.

3.2 Data generation approach

3.2.1 Background

Effective identification of household appliances requires a well-organized NILM. Considering the multi-facet nature of NILM, an efficient mathematical process is not the only critical factor. The prerequisite necessities and well-defined applications are significant inevitabilities of a valid NILM. Therefore, the investigation into the essential prerequisite of a NILM system has been the origin of the following studies. The importance of such an analysis has increased with the desire for a publicly available database that can account for exceptional electrical appliances in regions with specific weather conditions such as Quebec. In our case, these particular loads consist of ESH and EWH. The exploration of NILM prerequisites from one side and a suitable database from another side has revealed the necessity of a proficient database. Therefore, the proficiency of the database is the backbone of the provided analyses. This foundation has led to characterize the essential elements of a fruitful NILM from different aspects. In addition, it has resulted in the development of a framework capable of generating the synthetic data of appliances, for which real data is not available.

3.2.2 Methodology

The outcomes of the first study have been realized through two main steps. Initially, an extensive investigation into the characteristics of publicly available databases has been conducted. Afterward, a semi-synthetic data generator tool has been designated. The proposed procedure of semi-synthetic data generation and its simulation structure have been summarized in Figure 3-1. The mechanisms to develop this tool have been itemized below.

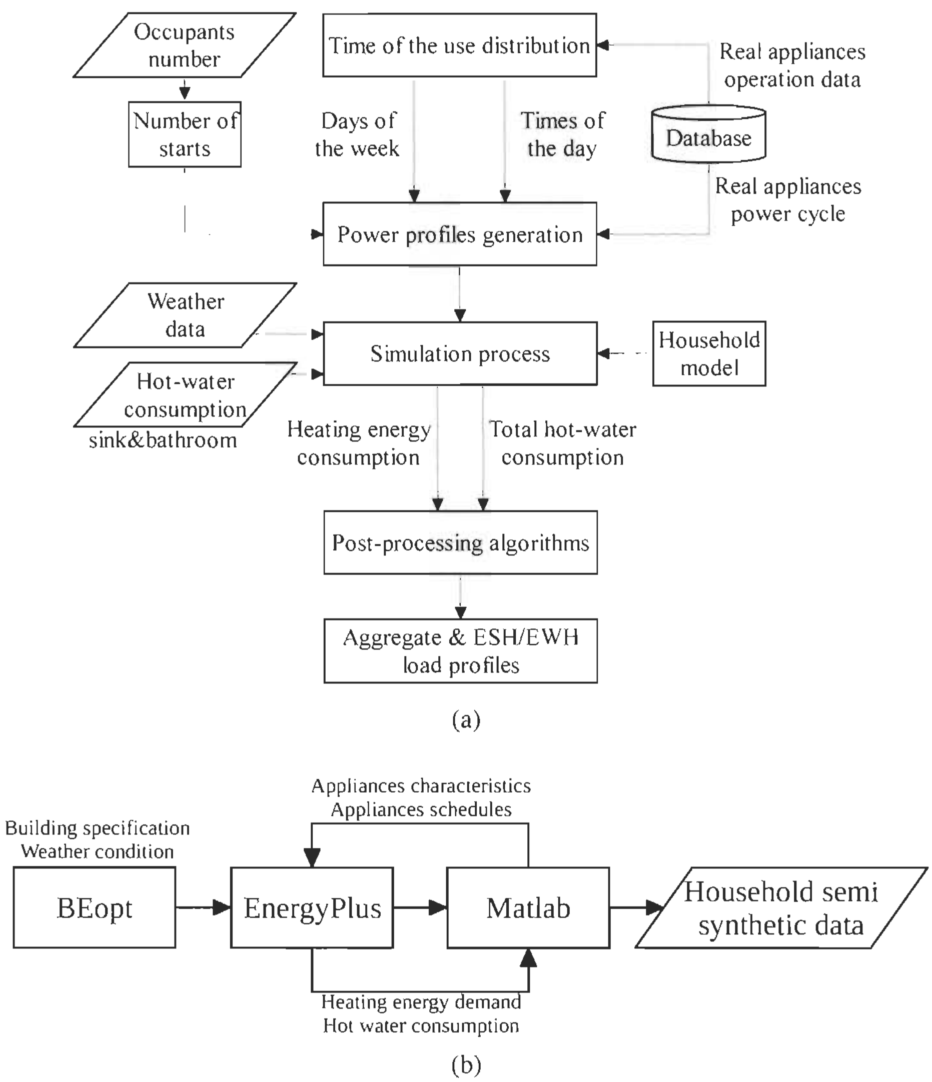


Figure 3-1 The block diagrams of (a) definite semi-synthetic data generator and (b) its simulation structure

- The probabilistic schedules of appliances operation are captured by using a circular Kernel Density Estimation (KDE), applied to real-world data from a public database.
- The long-term appliances power profiles are created by utilizing the probabilistic models and real active power signatures of the public database.
- These appliances are located in a house, modeled by Building Energy Optimization (BEopt) software that consists of two main zones. The modeled house accounts for thermal interactions, real weather data, and water consumption schedules from human activities like sink and bathroom.
- EnergyPlus software is utilized to simulate this architecture in order to find total power consumption, total heating system demand, and total hot water usage.
- Subsequently, a post processing phase is employed to generate the ON/OFF power profiles of heating appliances, ESH and EWH in this case, by exploiting related models of both types of appliances.

3.2.3 Outcomes

The study of NILM's essential elements and the exercise of appliances' synthetic data generation have brought about the followings.

- Defining the necessary features to design a proficient database for ALM studies.
- Creating effective load profiles of ESH and EWH based on their synthetic data, created by the data generation tool.
- Constructing an overall aggregated power profile by use of real appliances load profiles and synthetically generated ESH and EWH profiles that is similar to actual power profile of Quebec households.
- Demonstrating the challenges of ALM in Quebec households with the presence of ESH and EWH loads through a disaggregation analysis that has used HMM.

It is worth to mention that different cases can restrict the developed tool. For instance, simplified models of ESH and EWH can undermine their constructed two-state load profiles. Furthermore, in our analysis, due to the lack of a public database related to Quebec, appliances schedules from ECO database have been utilized. This can affect the practicality of the synthetically-generated load profiles of targeted loads because of possible differences between in-use devices and occupants' behavior in Quebec and the region where ECO data has been measured. Due to an extensive analysis, the framework of data generator tool is detailed in a complementary study. Therefore, the first analysis accounts for two related studies as below.

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Non-intrusive load monitoring through home energy management systems: A comprehensive review

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ABSTRACT

The enhanced utilization of Appliance Load Monitoring (ALM) in customer sites enabled by Home Energy Management Systems (HEMS) technologies, offers customized services and enables demand side flexibility in power systems. The significant integration of advanced electrical and computer engineering tools makes the nonintrusive approach of ALM a technically feasible solution to improve demand side energy utilization in the context of HEMS. This paper presents a comprehensive study conducted to reveal significant inevitabilities of a well organized Non-intrusive Load Monitoring (NILM) that aids Smart Home (SH) idea to be implemented. In fact, the viewpoint of this study is to discuss critical issues related to NILM prerequisite necessities, hindered the practical implication of this approach despite improvements during over 30 years. Accordingly, this work presents actual analyses in order to elucidate some arguments using state of the art procedures and results of a semi-synthetic data generator tool. In addition, with the aim of an achievable NILM, we analyze NILM applications from the stakeholders' perspective to assist the choice of employed techniques. Consequently, by investigating crucial intentions of an effective NILM considering current standstill and future progression, the authors propose the Advanced NILM (ANILM) concept and describe its properties to provide an enhanced energy usage system in demand side. In order to meet its ambition, the paper uses a realistic point of view to pinpoint major obstacles toward NILM and elaborate various factors that will make it effectively feasible.

1. Introduction

Smart grid, as an inevitable solution toward innovative energy management systems, is a key enabler for smart energy consumption in the future [1,2]. The significant interest in deploying effective energy management in demand side, due to national security concerns and social and economic benefits has its root in smart grid development, carbon dioxide emission reduction purposes, renewable energy resources integration, limited conventional energy resources, and growing trend of energy prices [3,4]. For instance, United States (US) primary energy, and electricity consumption in buildings is more than 38% and 76% respectively, which can be reduced up to 15–40% using a whole building energy management system [5].

Smart Home (SH) is the main conceptual archetype for demand side smart energy usage enabled by deriving the creation of a Home Energy Management System (HEMS) [1,3]. HEMS technologies can provide a mutual satisfaction between customers by realizing their comfort preferences and the utility by assisting energy saving strategies [6,7]. The emergence of an automation network offered by HEMS yields an advanced deployment of Appliance Load Monitoring (ALM) as the primary requirement to realize the SH platform [4]. It is noted that Department of Energy (DOE) defines SH on the edge of technologies with wider deployment and cost reduction in the coming years [8].

ALM can be executed using both intrusive and non-intrusive techniques. However, due to costly sub-metering installations, difficult upgrades settings, and customer privacy issues from one side, which hinder the former, as well as the integration of enhanced electrical and computer engineering tools from other side, which facilitates the latter; the non-intrusive approach is favored from both academic and industrial perspectives [9–11]. Non-intrusive Load Monitoring (NILM) technology is the practice of disaggregating household total electrical load measured at a single point into individual appliances signals, using the combination of an electrical acquisition system and signal processing algorithms [11,12]. NILM is considered as a high tech viable solution to achieve an improved demand side energy usage by contributing energy consumption feedbacks and progressive diagnosis mechanisms [4,7].

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NILM concept proposed by Hart [12] in 1992, has been studying for a long time however; it requires more progression to be regarded as a solved problem. NILM methods analyze the total signal through a routine process including event detection and feature extraction, as well as appliance classification and energy consumption estimation [4]. However, the proficiency in NILM techniques is one of the issues, which proves that more advanced disaggregating algorithms are required. From the standpoint of different approaches to the NILM procedures and mathematical algorithms, NILM has been already reported in literature. Zeifman and Roth [4] studied NILM with the focus of interest in signature examination for feature extraction as the first step of the general process. Tabatabaei et al. probed NILM mainly by concentrating on computational algorithms consisting of machine learning techniques for load disaggregation and classification as the second step of the common practice [13]. Zoha et al. reviewed NILM whole process presenting the same viewpoint as [4] regarding feature extraction step and moreover, discussing mathematical developments toward load disaggregation phase [14]. Without surveying NILM process, Alahakoon and Yu [1] investigated smart meter technologies to establish a data intelligence system in order to primarily realize utility concerns. Their study is regarded due to smart meters importance, as the hardware framework unavoidable for executing a part or entire NILM process. As a matter of fact, the revealed studies analyze technical and mathematical advances applied to the NILM common methods with different focuses. It is deduced that conducting an investigation intended to compare NILM methods and mathematical solutions where they are all case-specific and lack a standard evaluation process, is fruitless. However, the need for more efficient algorithms remains as a critical subject in order to design NILM systems that aim to recognize a wide range of household appliances with different electrical characteristics.

On the other side, there are other issues vital to achieve an adequate accuracy in order to design a practical NILM application, which have been neither studied nor fairly discussed in literature. Accordingly, in this study, we present a comprehensive survey with the aim of thoroughly evaluating these issues as significant factors toward realizing a feasible NILM. Unlike the prior arts, focusing on the methods analysis, the origin of this study is based on first, investigating the prerequisite necessities of an operative NILM and second, examining NILM applications as the fruits of its process to assist the choice of techniques. The analysis of these initial and final steps, which have been neglected by previous studies, result in comprehension of achievable NILM properties, contributed by authors in terms of Advanced NILM (ANILM).

Accordingly, this paper discusses major primary steps required for a successful NILM considering both technical and environmental concerns. Particularly, authors' discussion on the multi-faceted nature of NILM provides practical analyses to clarify the viewpoints on some related matters. The analyses are the results of a semi-synthetic dataset creator tool recently developed by authors, and NILM contemporary algorithms based on probabilistic methods. The semi-synthetic data generator platform is capable of deriving appliances probabilistic schedules and subsequently, simulating power demands of household heating/cooling systems and electric water heater in a modeled building [7]. Moreover, the probabilistic technique for NILM analysis is developed using Hidden Markov Models (HMM) as a concrete mathematical solution for recurrent pattern recognition and load classification [15–17]. Additionally, NILM applications as the end products of the NILM task are investigated from the participants i.e. the household customers and the system operator outlooks. NILM aspect is classified concerning the mutual priorities and interests of the stakeholders in order to examine practical approaches and represent an accurate detailed view on its applications with various intentions. Additionally, through a realistic vision, the authors thoroughly discuss noteworthy points regarding NILM to define future progresses. Correspondingly, this work prepares remarks, which will make NILM practically feasible by presenting the idea of ANILM and its features.

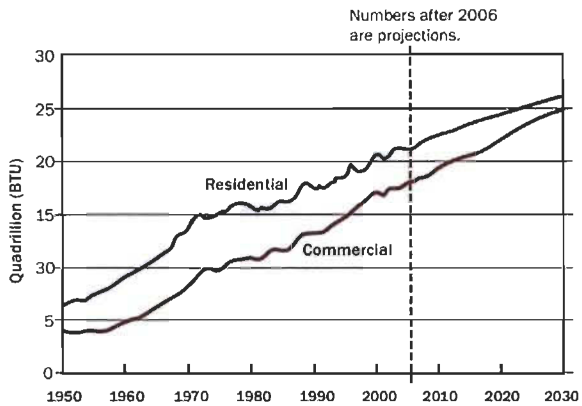

Fig. 1. Total primary energy consumption for building in US; Key: BTU=British Thermal Unit [19].

The rest of this study is organized as follows: Section 2 introduces NILM aspect and discusses critical issues toward an actual NILM using a detailed categorization. Section 3 provides the classification of NILM applications from the perspective of customer facilities and system operator interests. Section 4 analyzes the opportunities and challenges regarding the future of non-intrusive essence of ALM systems. The ANILM approach is presented in Section 5 followed by the concluding remarks in Section 6.

2. NILM concept

Population growth and increased standards of living are the main driving forces, which have caused an unavoidable growth of energy consumption [18,19]. The graph in Fig. 1 indicates the primary energy use (including that associates with electric use) of US residential and commercial sectors projected out to 2030 [19]. Therefore, the growing trend of energy usage necessitates the development of infrastructures for energy saving which is reinforced by government incentives and goals such as [19–22]:

- US federal government goal of using no more primary energy in 2030 than it does in 2008 by implementing a set of governments' policies and programs;
- US DOE goal of market-ready net-zero energy residential and commercial buildings in 2020 and 2025 by investing sufficient fund in R & D for next generation of building technologies;
- Canada's CamnetENERGY idea of Net Zero Energy (NZE) housing on the time horizon of 4 year research by the goal of drastically reducing the cost and risk of NZE technologies, and becoming readily available in market place.
- Canada's Energy Efficiency Regulation program of EnerGuide to reduce energy cost and emission by rating the energy efficiency of household appliances, heating and cooling equipment, new homes and vehicles, and making related information available to the public.

Accordingly, NILM as the promised type of ALM procedure receives a significant interest due to its capability to manage the energy consumption in demand side including residential and commercial buildings. Information collected from appliances' monitoring also assists to cope with more integration of fluctuating energy resources [23–25]. Moreover, NILM allows diagnosis and control of different loads connected to the grid and aids [24]:

- Customers to have valuable information of their individual appliances' energy consumption;
- System operators to analyze the energy flow in electric networks;

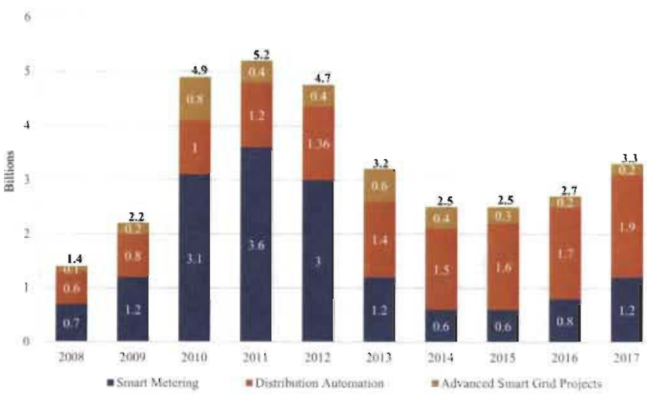

Fig. 2. Smart grid technologies' investment with projection to 2017 [5].

- Power markets to define public policies and tariffs;
- Manufactures to outline their orientation toward advanced appliances.

NILM approach can be implemented by any combination of physical hardware, metering equipment, and software including online and offline processes with the explicit intention of load disaggregation [26,27]. The online process, which accounts for feature extraction generally, includes metering, normalization, and event detection. On the other side, the offline practice comprises load modeling and identification, as well as energy evaluation [4,14,27]. Attention to the need for a compacted NILM system in the future, smart meters as the physical hardware should be defined as a compact entity consisting of both a metering device and a computation system [27]. Smart meters play a key role in the satisfactory achievements of NILM systems as they measure data samples to be utilized for load identification and energy estimation processes [15,28]. Advanced metering devices support two-way communication between the meter and the electricity supplier and interface with smart appliances, which in turn, allow utilities to better manage peak power demand and assist consumers to manage their own building energy use [29–31]. Fig. 2 shows that smart grid investment on smart meter technologies would continuously increase with a scope of 2017 [5]. Smart meters as the technical and actual description of ALM system will make NILM aspect practical in near future [32].

There are primary issues that can considerably influence both the intention of employing NILM and the results of executing NILM methods. A successful NILM should have an accurate and practical approach toward these concerns, which are investigated in the following.

2.1. Technical issues

Attention to appliances electrical characteristics, the methods of sampling their electrical signal, and the relationship between their operation patterns with occupants' behavior and environmental conditions, technical issues can be discussed from two major points that are addressed below.

2.1.1. Appliance classifications

In the first step, an explicit choice has to be carried out on appliance candidates. This has resulted in different load classifications represented in many researches based on their technical notions of proposed NILM analysis [33,34]. Regarding occupants' insights and appliances properties, these categorizations can be explained from four different points of aspect [33,34].

1. Customer perception: the most preferred classification considering the consumers' preference is to categorize appliances based on their role in the house, which refers to lighting appliance(s), kitchen/domestic appliance(s), and heating/cooling appliance(s) [10,33,35].
2. Operational state: this class reflects the number of appliance's steady state operations, which is preferable from the NILM perspective of load identification. This category consists of two-state appliances, multi-state appliances, continuously variable appliances, and permanent appliances. It is noted that active power properties of an appliance are utilized in order to define this class [10,14].
3. Waveform features: the creation of this category is based on the characteristics of voltage/current waveforms which comprises resistive appliances, electronically fed appliances, electronic power control appliances, pump-operated appliances, and motor-driven appliances [36].
4. User interface: self-activated appliances and user-activated appliances are the main subsets of this appliance set [5].

On the other side, from a wider and refreshing point of view, appliances can be categorized to consider system operator perspectives on their capabilities. Such an aspect, which is compatible with the energy management strategies offers the following appliances' practical categorization [23,25]:

1. Non-deferrable appliances: the electrical energy consumed by appliances in this class cannot be delayed such as lighting, cooking, and refrigerator. Although non-deferrable devices consume a considerable portion of energy in buildings, which their operation management can be advantageous to system operator, they are unable of providing power grid services due to inflexibility.
2. Deferrable appliances: this category consists of appliances like washing machine, and dryer that their electrical energy requirement can be postponed with regard to high energy demand hours. Particularly, this category represents thermostatic appliances with flexible demand capability, which account for a major portion of household total electricity demand [7,31,37]. Deferrable/Thermostatic Appliances (DTA) such as electrical water heaters, and space heating/cooling systems receive remarkable attention due to their specific advantages to offer power system facilities [37].

In fact, this categorization can direct NILM analysis toward beneficial applications and promote the choice of NILM algorithms since, the identification of a variety of household appliances is a burdensome practice and thus; NILM strategy should be well-defined and effective.

2.1.2. Dataset properties

Dataset contains household appliances information required for NILM process. Therefore, the dataset properties have a significant impact on the results of NILM practice [7]. Indeed, the efficiency of NILM technical processes highly depends on the quality and sufficiency of some crucial factors that should be met by measured database properties [7]. These factors, which can outline the efficacy of the real data, are termed in the following.

2.1.2.1. Data sampling interval. NILM should present a suitable technique for measuring the appliances' energy usage. Accordingly, two approaches can be differentiated for energy measurements in the domain of electric signal analysis and appliance identification [18,20,27,38,39]:

1. Low frequency: this method extracts features from long-term, i.e. minutes to hours or even days, power consumption data in a low sampling rate.
2. High frequency: this technique extracts features from short-term, i.e. cycles to seconds, voltage and current waveforms in a high sampling rate.

It is noted that there are different approaches to frequency ranges in order to define low and high rates and the choice of electrical signal as well [32]. Low frequency measurement techniques are regarded as they maintain a realistic aspect considering the actual smart meters' technologies, and big data handling concerns [15]. On the other side, higher sampling measures i.e. 10 kHz and up [32], require highly calibrated equipment for collecting data which are sensitive to electric noise however, they can provide important operative information for load identification [23,28]. Additionally, although a higher sampling frequency can allow for harmonic and signal transformation analysis of non-linear appliances with trivial low energy demand [40], it does not significantly improve the disaggregation results of high-usage resistive appliances [14,41].

More importantly, the desirable sampling frequency is determined considering the appliance candidates and load management goals [7]. Accordingly, a sampling time of 1 s to 1 min is generally utilized, by knowing the fact that 1 Hz sampled active power is accepted as the proper sampling interval [7]. From this standpoint, among the available public databases, only [11,42–44] provide this sampling resolution in both appliance and aggregate signal levels. However [45–47], offers higher sampling frequency just for aggregate signal. In fact, the measured sampling interval becomes challenging when the targeted appliances for NILM analysis require a higher sampling rate than the measured one to deliver more detailed information on electrical signatures.

2.1.2.2. The period of data measurement. Long-term available data is essential to analyze the correlation between household appliances operation with occupants behavior patterns and weather conditions [7]. Long-time information assists in investigating the impacts of the seasonal changes in terms of temperature variations on the household overall energy demand specifically seasonal appliances i.e. electrical heating and cooling systems [7]. This property can enhance NILM analysis and allow for not only appliance recognition but also discovering households energy consumption habits. Hence, there is only [43] which considers the sampling interval issue and also contains long-time data.

2.1.2.3. Appliance candidates principals. It is obvious that information of a dataset is case-specific including appliances with particular electric signature features [7]. Considering the importance of energy saving for both consumers and utilities, as one of the NILM ultimate purposes, a database should include the real data of appliances that consum a high portion of electric energy. Such energy demand can be drawn by different types of heating/cooling systems and Electrical Water Heaters (EWH) that have meaningful interactions with occupants activities, building gain and loss, and outside temperature which in turn, can aid NILM analysis [7]. However, most datasets give no information about major uses e.g. different heating/cooling systems and EWH demands [11,44,46]. One reason relates to the type of the utilized source for building heating demands which in such cases can be natural gas [47]. Generally, except for major kitchen appliances other loads considered in datasets are case-related and not among major usages [45].

2.1.2.4. Non-electric data. Non-electric features such as occupancy and indoor/outdoor temperature information can assist NILM analysis and form an enhanced load disaggregation practice [7]. Only DRED dataset [44] includes non-electric information in minute intervals, however, due to the way of storing data, this database requires a demanding preprocessing work to manage the appliances information compared to other databases like [11]. Moreover, it undergoes challenges including high rate of missing data e.g. outside temperature information, the lack of enough acquisition time period, and suitable information about heating/cooling appliances which almost makes temperature data useless to analyze. Actually, the accuracy of a signature-based study even by using proper electrical data can decrease due to electrical features sensitivity to different causes like temperature changes and thus; non-electric data matters as an important factor of a dataset [7].

Table 1
Publicly available datasets of household energy consumption [48].

Dataset	Number of houses	Measuring duration per house	Sampling frequency		Site
			Appliance	Aggregate	
REDD	6	3–19 days	3 s	1 s & 15 kHz	USA
BLUED	1	8 days	Event label	12 kHz	USA
GreenD	9	1 year	1 s	1 s	USA
ECO	6	8 months	1 s	1 s	DE
DRED [44]	1	6 months	1 s	1 s	USA
UMass Smart	3	3 months	1 s	1 s	UK
Tracebase	15	N/A	1–10 s	N/A	CDN
Pecan Street Sample	10	7 days	1 min	1 min	IND
HES	251	1–12 months	2–10 min	2–10 min	UK
AMPDs	1	1 year	1 min	1 min	AT/IT
iAWE	1	73 days	1–6 s	1 s	IND
UK-DALE	4	3–17 months	6 s	1–6 s & 16 kHz	CH
COMBED	8	18 months	30 s	30 s	NL
BERDS	N/A	1 year	20 s	20 s	USA
SustData	50	5 year	1 min	1 min	PT

Correspondingly, an applicable dataset should consider these major factors, which in turn, can facilitate the NILM operation. However, collecting all effective elements in a dataset is a burdensome task and in fact, publicly available databases that even realize the first two elements [43], does not generally include other elements i.e. major appliances information and non-electric data. Essentially, there is no a single household data with mentioned factors that incorporates the information of even all second level major appliances including refrigerator, washing machine, dryer, dishwasher, and stove which is another critical issue regarding the available databases. The information related to different public datasets is demonstrated in Table 1 considering the discussed issues [48].

2.2. Environmental issues

The environmental condition as the second issue is a crucial priority, which can significantly affect NILM purposes. Preferred appliances for NILM that should be mostly chosen base on the amount of energy consumption differentiate considering the environmental conditions. Indeed, a study on the seasonal weather and environmental conditions, which highly influence electricity consumption patterns, can effectively define energy saving strategies and in turn, rise interests in deploying NILM systems. For instance, the household appliances usage in the US and Canada is shown in Fig. 3 [5,49]. As it can be seen, weather condition causes a considerable difference in energy use preferences between these countries. In Canada, considering Quebec with cold long winters, heating appliances category including Electrical Space Heating (ESH) and EWH consume around 80% of households' total energy consumption [49]. It means that the most important part of energy saving practices can be met by managing ESH and EWH demands using NILM related methods. On the other hand, this category in the US consume around 31% of total energy usage which expresses that NILM task should also consider other major usages like space cooling.

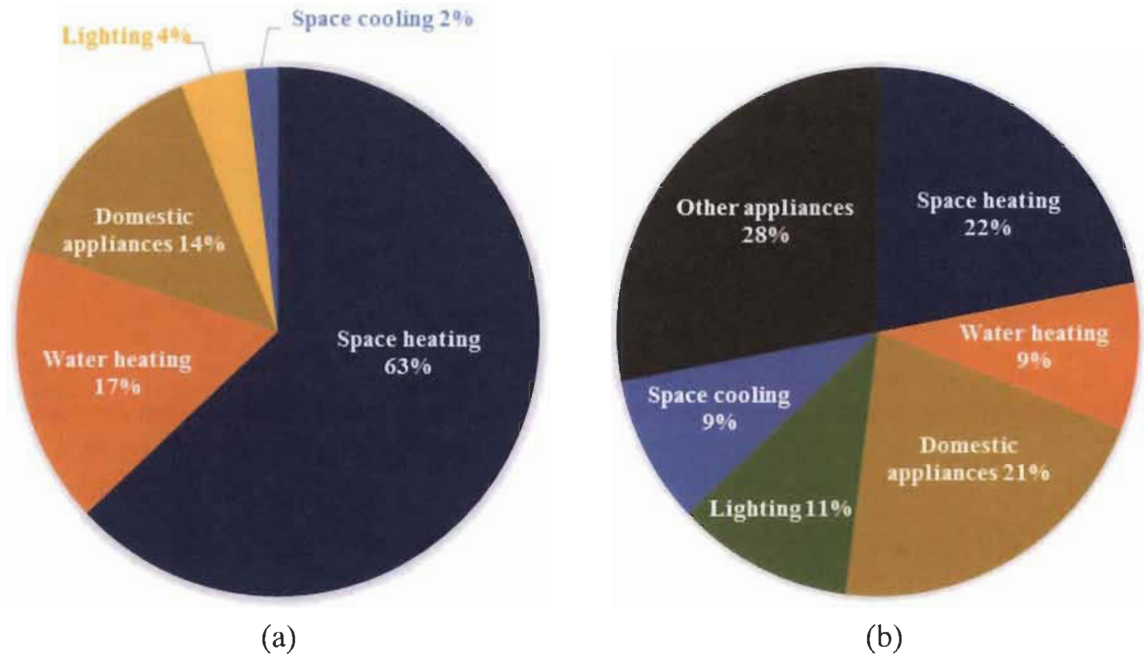

Fig. 3. Energy of end users as a percentage of total building energy use including electric usage in (a) Canada and (b) US [5,49].

Moreover, high energy demands, which can be due to environmental issues can bring about special NILM cases considering the type of in-use appliances. In Canada, household ESH systems encompass a high number of electric baseboards i.e. Quebec 61%, Newfoundland and Labrador 47%, New Brunswick 35%, Nova Scotia 22% [50] that can significantly confront the NILM operation. Electric baseboards have a high switching frequency that causes a large rate of temporal overlap. Furthermore, several electric baseboards located in each house may have the same nominal power that increases spatial overlapping events [7]. These issues along with the EWH short duration demands can decline NILM performance and so, a NILM system should be examined under such items in order to achieve a practical approach.

With the aim of enabling the practical analysis of such cases the author has developed a tool that can generate ESH and EWH synthetic data since, there is no publicly available data for Canadian cases. The semi-synthetic data generator can derive appliances probabilistic schedules from real datasets and then, creates their long-term power profiles using their real signatures. Subsequently, using a modeled house considering all thermal interactions, real weather data, and occupants water usage patterns, the tool synthetically creates on/off power demands of household heating/cooling systems and EWH [7] as shown in Fig. 4. The generated data from this tool is semi-synthetic since it utilizes both real power profiles and synthetic power loads to create the overall aggregated power profile.

In order to demonstrate the NILM challenges in the presence of electric baseboards and EWH, second level major appliances from ECO dataset [11] has been utilized as real data to produce the on/off power profiles of 11 baseboards and one EWH in a modeled house [7]. Fig. 5 illustrates created semi-synthetic and real aggregated power profiles using the information of ECO house number one in the same day. It is observed that, the resulted power profile in the presence of electric baseboards and EWH can be a difficult case for NILM analysis. The reason is that, it includes a great number of on/off transition events, which increase the rate of both temporal and spatial overlapping [7]. Moreover, the operation cycle of electric baseboards and EWH is short which causes difficulties for NIM methods that seek a sufficient operating time for the training step [7,13].

The developed tool has a realistic viewpoint since, it captures the operation schedules and power signatures from a real world data and distributes appliances in a modeled house considering thermal gain and loss due to inside/outside temperature variations in order to simulate ESH and EWH load consumption [7]. Additionally, a load

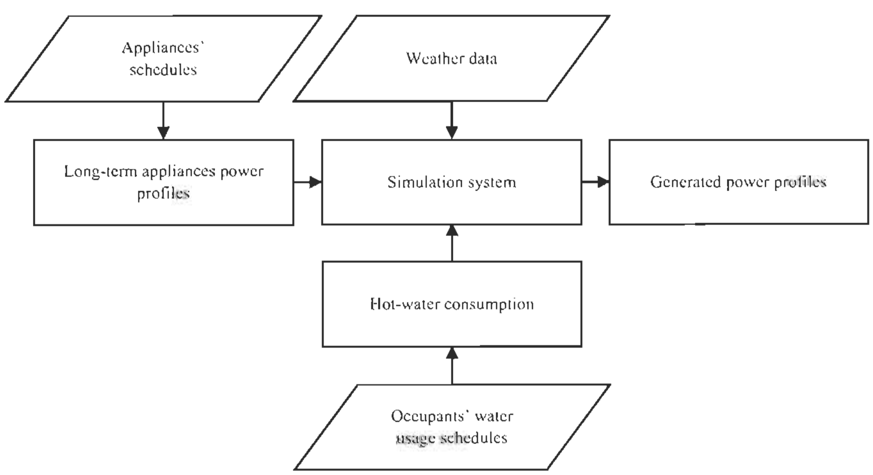

Fig. 4. The structure of the semi-synthetic data generator tool.

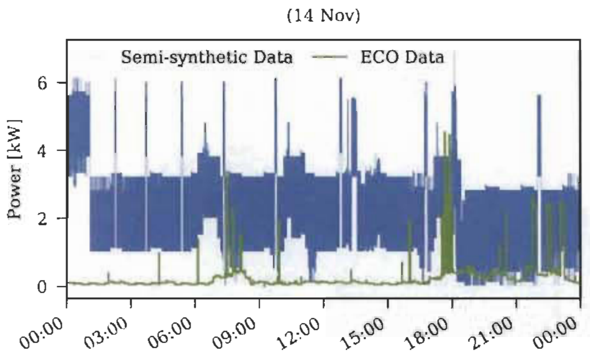

Fig. 5. Semi-synthetic and ECO daily aggregated power profiles generated using the information of ECO second level appliances data.

Table 2
The accuracy score of disaggregating refrigerator in different scenarios.

Scenarios	ECO	EWH presence	One electric baseboard presence	Two electric baseboards presence
Disaggregation accuracy	96%	95%	74%	71%

disaggregation procedure has been developed to actually indicate the impact of electric baseboards and EWH presence on NILM practice to identify household appliances. In this regard, HMM as an advanced and robust algorithm has been utilized for pattern recognition and load identification [15,16,18,51,52]. The Viterbi algorithm as a dynamic programming procedure has been used to compute the most probable hidden state of HMM and solve the disaggregation problem [52]. Table 2 shows the accuracy results of disaggregating refrigerator in four different scenarios using appliance-based accuracy score [14,53]. After simulating on/off power profiles of electric baseboards and EWH, their signature has been increasingly presented in the ECO aggregated load profile. It can be seen that the ability to recognize refrigerator continuously decreases in the presence of ESH and EWH. The accuracy reduction even with a few number of electric baseboards is considerable which evidences NILM difficulties with real cases of several in-use baseboards.

The detailed discussion presented above with actual study demonstrates the importance of appliance candidates and environmental issues as major effective factors in NILM analysis. Accordingly, HEMS should account for these effective issues, if possible in order to realize an operative NILM, which can lead to household appliances correct monitoring and energy demand savings [16].

3. Classification of NILM applications

Given the fact that NILM has been discussed so many years focusing on proposed methods, this literature attempts to present the perspective of NILM applications concerning customer preferences and system operators' interests. Indeed, defining the application of ALM can assist the choice of NILM techniques and appliance candidates, which in turn, facilitates and improves the NILM task. For instance, if the NILM application is to monitor non-linear loads, the transient analysis of current waveforms of such appliances like microwave and computer in higher sampling rate is preferred [14,54]. This aspect can categorize NILM utilizations in two sections described in the following. It is noted that energy saving as the foundation of NILM is the mutual concern of both customers and system operator and thus; the common application of NILM systems [32].

3.1. Customer-side NILM applications

This category presents fields in which NILM feedbacks please customers by providing convenient services as below:

3.1.1. Intelligent thermostatic control systems (ITCS)

Advances in communication and electronic technologies have introduced the communicating electronic thermostatic systems to give customers the ability to remotely manage their operations such as heating systems. These systems have received significant attention because of their wide availability and ability to be toggled on/off without compromising end user satisfaction [55,56]. Moreover, high tech advancements in terms of Internet of Things (IoT), cloud computing, and big data cause to take a great advantage of ITCS to facilitate customers living manners [1]. Subsequently, through controlling electric energy consumption, thermostatic systems can provide a wide range of grid services regarding system operator interests still maintaining user comfort [55].

On the other hand, existing NILM methods undergo difficulties in the presence of the electronic thermostatic loads operating in short periods of a few seconds that specifically affect the NILM training processes [5,13]. Consequently, NILM approaches should be able to handle technical barriers associated with ITCS, which has not usually been investigated in literature.

3.1.2. Failure analysis and security management

A promising use of NILM technology is to locate and identify device failures or abnormal usages which can be evidenced by unusual power consumption or duty cycle characteristics [25,27]. Security management enabled by NILM is another remarkable utilization, since with new generation of smart meters capable of providing highly accurate profiles of energy usage, it is possible to identify consumers' specific activities or behavior patterns, which brings about serious privacy concerns [23,25,57,58]. Therefore, providing a trade-off between smart meter information privacy and its applications particularly for grid services, can satisfy the participants [25,57]. The proposed approaches to address such arrangement are generally based on the anonymization of meter readings. Gong et al. has studied the cryptographic primitives technique to verify customer information for participating in grid services without uncovering their actual identity [57]. Yang et al. has explored a method based on covering the data using a rechargeable battery to provide a consistent consumption that is equivalent to customer's average usage [9]. Other typical methods for data preserving are based on providing uncertainties in the total power signal which require technical changes in smart meters structures [9]. Indeed, failure, abnormal or high consumption detection, security management, and computerized surveillance specifically remotely are important opportunities allowed by NILM.

3.2. Grid-side NILM applications

NILM as an adaptive enabling technology can facilitate power grid services that interest system operator. The automation network enabled by NILM mechanisms can enhance HEMS communication with different type of appliances to gather their power consumption data [59]. NILM capability in load disaggregation and energy computation can provide an advantageous application for HEMS to manage economic development, and pattern recognition of occupants' behavior [3,59,60]. Accordingly, HEMS can participate in power grid services by employing NILM systems [59]. Lin and Tsai [59] have utilized NILM in the context of a HEMS to execute a residential Demand Response (DR). In fact, the general approach to NILM application for grid services is the management of household appliances to engage in DR and Demand Side Management (DSM) programs [9,25,57,61]. Alizadeh et al. have studied the potential of DTA for DR which is regarded as a promising NILM application to take the advantage of DTA capabilities in demand side [25]. In addition, NILM exploitation for DSM services can provide estimates on energy savings as well as end-use load profiles [23,60]. It is deduced that there is a significant potential for enhancing grid services using NILM, which requires to be more investigated.

4. The future standpoint of NILM: deadlock or progress

Indeed, this survey attempts to reveal pivotal challenges regarding NILM systems in order to give meaning to future opportunities. Most of the researchers believe that the traditional application of NILM for energy auditing has come to a halt [60,62]. This lack of progress can be described within two main argumentations as below.

4.1. Advancement of smart grid adapting technologies

The first reason for lapses in NILM is more about the causes of tendency to this concept at the first place. NILM has been presented as a viable alternative to the home automation network because of two important facts:

4.1.1. Lack of communication infrastructure and customer affinity

The lack of a two-way communication with each home appliance as well as social acceptance of home automation network are the first persuasive evidence for employing non-intrusive aspect [4]. Therefore, new advancement in Advanced Metering Infrastructure (AMI) technologies, revolutionary changes in power networks under smart grid paradigm, and growing rate of customer's affinity for new developments, can impose difficulties for the future acceptance of NILM approach as a preferred alternative solution.

4.1.2. Smart plugs/outlets high cost

Smart outlets represent an intrusive aspect of load monitoring systems that can be installed for each building's appliance. Utilization of NILM during years can also be attributed to the high cost of smart outlets [62]. However, the mainstream of home automation sector equipped with the low cost smart outlets capable of remote load control is expected to continue remaining more relevant than non-intrusive concept in the future, growing by 60% from 2012 to 2018 [26]. This trend conveys the message that these convenient technologies may replace the non-intrusive systems [26,62]. Nevertheless, the smart outlet technology faces some difficulties like errors that come from the poor performance of the electronic devices that need proper solutions [14,26,62].

4.2. NILM technical barriers

Considering the essence of NILM approach, technical issues are vital obstacles for future development. Accordingly, the lack of new progresses despite numerous proposed solutions can be viewed from two different points. Internal difficulties, which includes complexity of the load space, and proficiency of the available data as well as external difficulties, that consists of the lack of a standard for data acquisition, the absence of unified evaluation systems, human intervention barriers, and case-specific studies incapable of generalization [4,7,14,61,62]. As noted, although technical problems of NILM have been explored for many years, serious concerns exist which have not been thoroughly solved [61,62].

Apart from above, new outlooks are undertaken to provide a progressive idea in order to overcome the deadlock of NILM applications. The new perspective outlines NILM system with a reasonable complexity which utilizes an appropriate data for a specific application [7,61]. Accordingly, two opposite aspects toward the future research on NILM can be inferred [61,62]:

- Positive views believe that with a more reasonable, less complex approach toward a progressive NILM concept deviated from prior ineffective ideas, novel thoughts, and studies will be established.

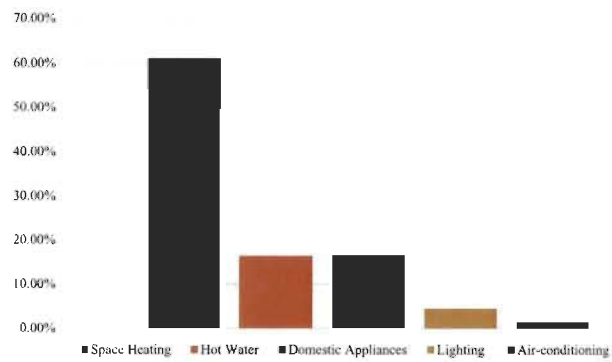

Fig. 6. Breakdown of household energy consumption by type of use in Quebec, Canada in 2011.

- Negative views believe that it is impractical to identify household appliances solely using a non-intrusive approach based on the measurement of one dimension signal at a single point.

5. The creation of ANILM systems

In order to make progressive views toward NILM achievable, the ANILM concept is proposed. Given the NILM discussion in previous sections, it is realized that an ANILM system should consider significant properties described as below.

5.1. DTA utilization

ANILM should account for appliance candidates that are first among major consumption devices and second able to be delayed. These factors refer to DTA, which are important for both demand and supply sides' scenarios [25,37]. These appliances are capable of providing grid services without jeopardizing the quality and reliability of their primary function according to users' comfort level, and satisfaction [25,55,63]. For instance, Fig. 6 demonstrates residential energy usage in Quebec, Canada in 2011 [64]. As it can be seen, DTA such as ESH and EWH consume more than 70% of household total energy use, which reveals their great potential to provide power grid facilities that satisfy both customers and utilities. The same scenario can be realized for space cooling devices as DTA in the US, shown in Fig. 3. Therefore, ability to exploiting DTA potentials as Medium Energy Storages (MES) in demand side is an important feature of an ANILM. For example, DTA by means of ANILM systems can facilitate more integration of small scale renewable energy resources in the near future [55,64–67]. Such perspective represents DTA as grid friendly appliances with a range of advantages for both customers through delivering incentives and suppliers through providing grid services.

5.2. Real-time application

Furthermore, ANILM should realize a real-time structure as an inevitable part of future power networks under smart grid paradigm. Moreover, the real-time aspect of ANILM is essential considering the new movement of technology toward different designs such as IoT environment that provide an enhanced communication among utilities, manufactures, and customers [1,15,16,32]. It should be mentioned that traditional NILM concept with a huge complicated space of data, slow analysis process, and long computational time is usually an off line system. In fact, the idea of ANILM can enable utilization of DTA capabilities in a real-time context. Furthermore, this concept can provide a practical indoor communication with DTA and other MES such as Plug in Electric Vehicles (PEVs), and renewable energy resources as well as a beneficial outdoor communication with system operator.

6. Conclusion

The promise of Non-Intrusive Load Monitoring (NILM) approach eases the effective cooperation among stakeholders in electrical energy industry in the context of Home Energy Management System (HEMS) and gives a new force to inevitable move toward Smart Home (SH) concept. Accordingly, in this paper we conducted a thorough study on major issues required to achieve an actual NILM. Apart from the methods analyses, the paper investigated the prerequisite necessities and final constructive expectations of the NILM system in order to realize an effective NILM. Initial requirements to establish a well-organized NILM were described using concrete analyses to address some important issues. Furthermore, the paper explored the primary applications of NILM considering both customer and utility sides to develop an operative NILM structure in terms of utilized mechanisms. From a realistic standpoint, the author proposed the Advanced NILM (ANILM) aspect and discussed its properties as the result of a clear understanding of an effective NILM requirements and purposes. ANILM concept can lead to a building with integrated system designs and operations. A successful realization of this concept eventually makes HEMS feasible. ANILM abilities which can make actual NILM applications feasible, can be considered as the solution for regressive trend of traditional NILM and create a novel way for next studies.

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References

[1] Alahakoon D, Yu X. Smart electricity meter data intelligence for future energy systems: a survey. IEEE Trans Ind Inform 2016;12:425–36.
[2] Hosseini SS, Badri A, Parvania M. A survey on mobile energy storage systems (MESS): applications, challenges and solutions. Renew Sustain Energy Rev 2014;40:161–70.
[3] Hu Q, Li F, Chen C. A smart home test bed for undergraduate education to bridge the curriculum gap from traditional power systems to modernized smart grids. IEEE Trans Educ 2015;58:32–8.
[4] Zeifman M, Roth K. Nonintrusive appliance load monitoring: review and outlook. IEEE Trans Consum Electron 2011;57:76–84.
[5] US Department of Energy . An assessment of energy technologies and research opportunities. USA, Washington D.C: US Department of Energy; 2015.
[6] Paris J, Donnal J, Remscrim Z, Schantz C, Kirtley JL, Leeb SB, et al. Non-intrusive induction motor speed detection. IET Electr Power Appl 2015;9:388–96.
[7] Hosseini SS, Agbossou K, Kelouwani S, Cardenas A, Henao N. A Semi-synthetic dataset development tool for household energy consumption analysis. In: Proceeding of IEEE 18th annual international conference industrial technology; 2017. p. 564-9.
[8] US Department of Energy . Revolution...now: the future arrives for five clean energy technologies. USA, Washington D.C: US Department of Energy; 2015.
[9] Yang L, Chen X, Zhang J, Poor HV. Cost-effective and privacy-preserving energy management for smart meters. IEEE Trans Smart Grid 2015;6:486–95.
[10] Ridi A, Gisler C, Hennebert J. Automatic identification of electrical appliances using smart plugs. In: Proceedings of the IEEE 8th international workshop systems, signal processing and their applications; 2013. p. 301–5.
[11] Beckel C, Kleiminger W, Cicchetti R, Staake T, Santini S. The ECO data set and the performance of non-intrusive load monitoring algorithms. In: Proceedings of the 1st ACM conference on embedded systems for energy-efficient buildings USA: ACM Press; 2014. p. 80–9.
[12] Hart GW. Nonintrusive appliance load monitoring. Proc IEEE 1992;80:1870–91.
[13] Tabatabaei SM, Dick S, Xu W. Towards non-intrusive load monitoring via multi-label classification. IEEE Trans Smart Grid 2016;3053, [1–1].
[14] Zoha A, Gluhak A, Imran M, Rajasegarar S. Non-intrusive load monitoring approaches for disaggregated energy sensing: a survey. Sensors 2012;12:16838–66.
[15] Guo Z, Wang ZJ, Kashani A. Home appliance load modeling from aggregated smart meter data. IEEE Trans Power Syst 2015;30:254–62.
[16] Egarter D, Bhuvana VP, Elmenreich W. PALDi: online load disaggregation via particle filtering. IEEE Trans Instrum Meas 2015;64:467–77.
[17] Pöchacker M, Egarter D, Elmenreich W. Proficiency of power values for load disaggregation. IEEE Trans Instrum Meas 2016;65:46–55.
[18] Aiad M, Lee PH. Unsupervised approach for load disaggregation with devices interactions. Energy Build 2016;116:96–103.
[19] American Energy Society . Energy future: think efficiency. California, USA: American Energy Society; 2008.
[20] Du L, Yang Y, He D, Harley RG, Habetler TG. Feature extraction for load identification using long-term operating waveforms. IEEE Trans Smart Grid 2015;6:819–26.
[21] Natural Resources Canada . Housing research. Ottawa, Canada: Natural Resources Canada; 2014.
[22] Natural Resources Canada . Choosing and using appliances with EnerGuide. Ottawa, Canada: Natural Resources Canada; 2013.
[23] Basu K, Debusschere V, Bacha S, Maulik U, Bondyopadhyay S. Nonintrusive load monitoring: a temporal multilabel classification approach. IEEE Trans Ind Inform 2015;11:262–70.
[24] Lin YH, Tsai MS. Development of an improved time-frequency analysis-based nonintrusive load monitor for load demand identification. IEEE Trans Instrum Meas 2014;63:1470–83.
[25] Alizadeh M, Scaglione A, Applebaum A, Kesidis G, Levitt K. Reduced-order load models for large populations of flexible appliances. IEEE Trans Power Syst 2015;30:1758–74.
[26] Butner R, Reid D, Hoffman M, Sullivan G, Blanchard J. Non-intrusive load monitoring assessment: literature review and laboratory protocol. USA, Washington D.C: US Department of Energy; 2013.
[27] Basu K, Debusschere V, Douzal-Chouakria A, Bacha S. Time series distance-based methods for non-intrusive load monitoring in residential buildings. Energy Build 2015;96:109–17.
[28] Barker S, Kalra S, Irwin D, Shenoy P. Empirical characterization, modeling, and analysis of smart meter data. IEEE J Sel Areas Commun 2014;32:1312–27.
[29] Kabalci Y. A survey on smart metering and smart grid communication. Renew Sustain Energy Rev 2016;57:302–18.
[30] Leiva J, Palacios A, Aguado JA. Smart metering trends, implications and necessities: a policy review. Renew Sustain Energy Rev 2016;55:227–33.
[31] Perez KX, Cole WJ, Rhodes JD, Ondeck A, Webber M, Baldea M, et al. Nonintrusive disaggregation of residential air-conditioning loads from sub-hourly smart meter data. Energy Build 2014;81:316–25.
[32] Carrie Armel K, Gupta A, Shrimali G, Albert A. Is disaggregation the holy grail of energy efficiency? The case of electricity. Energy Policy 2013;52:213–34.
[33] Seo Y-K, Hong W-H. Constructing electricity load profile and formulating load pattern for urban apartment in Korea. Energy Build 2014;78:222–30.
[34] Wichakool W, Remscrim Z, Orji UA, Leeb SB. Smart metering of variable power loads. IEEE Trans Smart Grid 2015;6:189–98.
[35] Trung KN, Dekneuvel E, Nicolle B, Zammit O, Van CN, Jacquemod G. Using FPGA for real time power monitoring in a NIALM system. In: Proceedings of the IEEE international symposium on industrial electronics; 2013. p. 1–6.
[36] Pérez MNV. A non-intrusive appliance load monitoring system for identifying kitchen activities. department of automation and systems technology. Finland: Aalto University; 2011.
[37] Xu Z, Diao R, Lu S, Lian J, Zhang Y. Modeling of electric water heaters for demand response: a baseline PDE model. IEEE Trans Smart Grid 2014;5:2203–10.
[38] Henao N, Agbossou K, Kelouwani S, Dube Y, Fournier M. Approach in nonintrusive type I load monitoring using subtractive clustering. IEEE Trans Smart Grid 2015;8:812–21.
[39] Chen Z, Wu L. Residential appliance DR energy management with electric privacy protection by online stochastic optimization. IEEE Trans Smart Grid 2013;4:1861–9.
[40] Hassan T, Javed F, Arshad N. An empirical investigation of V-I trajectory based load signatures for non-intrusive load monitoring. IEEE Trans Smart Grid 2014;5:870–8.
[41] Wong YF, Ahmet Sekercioglu Y, Drummond T, Wong VS. Recent approaches to non-intrusive load monitoring techniques in residential settings. In: Proceedings of the IEEE Computational Intelligence in Smart Grids; 2013. p. 73–9.
[42] Barker S, Mishra A, Irwin D, Cecchet E, Shenoy P, Albrecht J. Smart*: an open data set and tools for enabling research in sustainable homes; 2012. (http://traces.cs.umass.edu/index.php/Smart/Smart). [Accessed 17 April 2002].
[43] Monacchi A, Egarter D, Elmenreich W, D'Alessandro S, Tonello AM. GREEND: an energy consumption dataset of households in Italy and Austria. In: Proceedings of the IEEE international conference on smart grid communications; 2014. p. 511–6.
[44] Uttama Nambi ASN, Reyes Lua A, Prasad VR. LocED: location-aware energy disaggregation framework. In: Proceedings of the 2nd ACM International conference on embedded systems for energy-efficient built environments USA: ACM Press; 2015. p. 45–54.
[45] Kolter JZ, Johnson MJ. REDD: a public data set for energy disaggregation research. In: Proceedings of the workshop on data mining applications in sustainability USA; 2011. p. 1–6.
[46] Anderson K, Ocneanu AF, Benitez D, Carlson D, Rowe A, Bergés M. BLUED : a fully labeled public dataset for event-based non-intrusive load monitoring research. In: Proceedings of the 2nd KDD workshop on data mining applications in sustainability China; 2012. p. 1–5.
[47] Kelly J, Knottenbelt W. The UK-DALE dataset, domestic appliance-level electricity demand and whole-house demand from five UK homes. J Sci Data 2015;2:150007.
[48] Bonfigli R, Squartini S, Fagiani M, Piazza F. Unsupervised algorithms for non-intrusive load monitoring: An up-to-date overview. In: Proceedings of the IEEE 15th international conference on environment and electrical engineering; 2015. p. 1175–80.
[49] Natural Resources Canada. Energy efficiency trends in Canada 1990 to 2009. Ottawa, Canada: natural resources Canada; 2011.
[50] Statistics Canada. Canada's national statistical agency. Households and the environment: energy use analysis 2007; 2012. (http://www.statcan.gc.ca/pub/11-526-s/2010001/part-partie1-eng.htm). [Accessed 17 April 2002].
[51] Johnson MJ, Willsky AS. Bayesian nonparametric hidden semi-Markov models. J Mach Learn Res 2013;14:673–701.

[52] Egarter D, Bhuvana VP, Elmenreich W. PALDi: online load disaggregation via particle filtering. Instrum Meas IEEE Trans 2015;64:467–77.
[53] Liang J, Ng SKK, Kendall G, Cheng JWM. Load signature studypart I: basic concept, structure, and methodology. IEEE Trans Power Deliv 2010;25:551–60.
[54] Lin Y-H, Tsai M-S. Development of an improved time–frequency analysis-based nonintrusive load monitor for load demand identification. IEEE Trans Instrum Meas 2013;63:1470–83.
[55] Kara EC, Bergés M, Hug G. Impact of disturbances on modeling of thermostatically controlled loads for demand response. IEEE Trans Smart Grid 2015;6:2560–8.
[56] Sala E, Kampouropoulos K, Prieto MD, Romeral L. Disaggregation of HVAC load profiles for the monitoring of individual equipment. In: Proceedings of the IEEE 21st international conference emerging technologies and factory automation; 2016. p. 1–6.
[57] Gong Y, Cai Y, Guo Y, Fang Y. A privacy-preserving scheme for incentive-based demand response in the smart grid. IEEE Trans Smart Grid 2016;7:1304–13.
[58] Zhou B, Li W, Chan KW, Cao Y, Kuang Y, Liu X, et al. Smart home energy management systems: concept, configurations, and scheduling strategies. Renew Sustain Energy Rev 2016;61:30–40.
[59] Lin Y-H, Tsai M-S. An advanced home energy management system facilitated by nonintrusive load monitoring with automated multiobjective power scheduling. IEEE Trans Smart Grid 2015;6:1839–51.
[60] Hu Q, Li F. Hardware design of smart home energy management system with dynamic price response. IEEE Trans Smart Grid 2013;4:1878–87.
[61] He D, Lin W, Liu N, Harley RG, Habetler TG. Incorporating non-Intrusive load monitoring into building level demand response. IEEE Trans Smart Grid 2013;4:1870–7.
[62] Barker S, Musthag M, Irwin D, Shenoy P. Non-intrusive load identification for smart outlets. IEEE Int Conf Smart Grid Commun 2014:548–53.
[63] Pourmousavi SA, Patrick SN, Nehrir MH. Real-time demand response through aggregate electric water heaters for load shifting and balancing wind generation. IEEE Trans Smart Grid 2014;5:769–78.
[64] Hydro-Québec. Sustainability report 2014. Québec, Canada: Hydro Québec; 2015.
[65] Huang L, Hjalmarsson H. A Multi-Time-Scale Generalization of Recursive Identification Algorithm for ARMAX Systems. IEEE Trans Autom Control 2015;60:2242–7.
[66] Nguyen DT, Le LB. Joint optimization of electric vehicle and home energy scheduling considering user comfort preference. IEEE Trans Smart Grid 2014;5:188–99.
[67] Zhang Y, Lu N. Parameter selection for a centralized thermostatically controlled appliances load controller used for intra-hour load balancing. IEEE Trans Smart Grid 2013;4:2100–8.

A Semi-Synthetic Dataset Development Tool for Household Energy Consumption Analysis

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***Abstract*—Home Energy Management System (HEMS) is acknowledged as a promised approach to explore household appliances dynamic energy usage. The availability of an appropriate dataset is indispensable to evaluate the performance of HEMS operations in the designing phase. In this paper, we develop a tool capable of generating long-term semi-synthetic data to avoid deficiency of available datasets particularly, the lack of the major appliances measurements and non-electric information. Accordingly, a simple household with primary appliances located in two-main zones is simulated. The paper utilizes a statistical analysis of real-world data to create probabilistic models of appliances and consequently, produce time-extended stochastic power profiles. Afterward, a simulation structure is developed to generate the power consumption profiles of major appliances consisting of Electrical Space Heaters (ESH) and Electrical Water Heaters (EWH). In order to achieve its ambition, this study executes a post-processing practice to create on/off power profiles of these appliances using their models. The results show that the proposed tool can be exploited for different HEMS scenarios.**

I. Introduction

Smart grid development bolsters the interests in deploying HEMS in demand side due to enabling the idea of smart home in the near future [1], [2]. Smart home facilitates occupants comfort in the building while saving the energy through realizing an advanced sensing and measurement system as one of the five fundamental technologies essential for the smart grid [3]. The emergence of HEMS technologies can be considered as the primary requirement to realize the smart home platform [4]. These technologies assist residential dynamic power consumption analysis by providing load monitoring and energy usage feedback, as well as advanced control and diagnosis. For instance, load monitoring services allow energy usage regulation, fault/abnormal usage detection, elderly surveillance and intrusion verification, especial and emergency situation recognition, and novel electric bills preparation [5]–[9].

Correspondingly, the availability of an appropriate dataset is the fundamental requirement to conduct a valuable HEMS investigation in residential buildings [10]. Such dataset is highly beneficial to the approach of Non-Intrusive Load Monitoring (NILM) which facilitate HEMS, since this technique seeks suitable information in order to deliver useful results. NILM is regarded as an effective application of an advanced HEMS [11]. It is deduced that an appropriate dataset would consist of a real-world data that its properties concern all possible elements which affect the performance of residential energy analysis techniques. Notwithstanding, amassing such dataset is costly, time-consuming, and cumbersome [12] thus; a more comprehensive dataset from both perspectives of electric and non-electric information, even not completely real, can be defined as a promised database for HEMS services examination.

Moreover, propriety of a dataset depends on the geographical characteristics and thus the type of in-use appliances, particularly electric heating and cooling devices. In countries with cold winter climates like Canada, ESH and EWH controlled by electronic thermostats demanding high energy rate i.e. more than 80%, generate specific challenging HEMS scenarios specifically for NILM techniques [13]. However, majority of available datasets are measured in US and European countries [10], that boosts the ambition of this study to contribute a tool for data generation which in turn can be used for the exceptional cases of Canada like Quebec region.

Accordingly, in this study, we intend to develop a tool capable of generating time-extended semi-synthetic data to deal with challenges regarding the collection of real-world data. This paper explores household appliances actual data to characterize their consumption behavior by means of a statistical analysis. The usage patterns are learned with no prior information, to realize appliances probabilistic models which in turn are used to produce time-extended stochastic power profiles. Subsequently, the created signals of real power signatures are exploited to generate synthetic data of major appliances in the context of a simulation framework. These major appliances include Electrical Space Heaters (ESH) and Electrical Water Heaters (EWH). Finally, a post-processing phase is applied to create ESH and EWH on/off load profiles. The semi-synthetic aggregated power profile is the ultimate result of the whole analytical method and simulated system.

The rest of this study is organized as follows: Section 2 discusses a brief discussion over public datasets. The statistical analysis of real-world data in order to capture appliances schedules is described in section 3. Moreover, the simulation structure to generate the synthetic data is developed in this section. Section 4 presents the results and relating analyses over them which is followed by a conclusion in section 5.

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II. Background and Contribution

Considering the characteristics of the existence databases mainly for NILM purposes, there are significant elements that define the usefulness of a dataset discussed as below:

1- Granularity of the data: Acceptable granularity for the dataset depends on targeted appliances and the aim of investigating them. Nonetheless, the tendency is to utilize a sampling period of 1 second to 1 minute [10] with a common belief that selected electrical features should be 1Hz-sampled active power [14]. Higher resolution data and other electric features may provide effective and flexible signature analysis, but there are some important issues to notice. First, it increases the set-up costs and also the size of information which would be difficult to manage. Second, such information may not be compatible with smart meter technologies [15], [16].

2- Time duration of data acquisition: Time-extended data measurements is significantly important in order to study the impacts of the occupants' behavior and weather changes on electricity demand [10]. Analyzing the relationship between appliances energy usage especially major seasonal appliances and non-electric information requires a time-extended information to apply explicable results [11]. In fact, understanding of consumer activities and environmental conditions are crucial for developing an advanced NILM analysis [17], [18].

3- Non-electric information: The information referred to as non-electric can improve HEMS services particularly NILM in the context of a multi-modal load identification procedure [19]. The importance of providing non-electric data e.g. outside temperature increases by knowing that even high-resolution signature analysis declines as electrical characteristics change under situations like temperature variations.

4- Appliance candidates criteria: The inflexible information of datasets includes specific manufactured appliances which have their particular electric features [20]–[22]. Therefore, an acceptable dataset should consist of common household appliances with a considerable share of electricity consumption that have an effective relationship with occupants behavior and environmental situations. These appliances generally include different heating/cooling systems and EWH [13].

In this regard, an actual dataset with the properties of sufficient acquisition time i.e. yearly and proper sampling frequency i.e. at least one second is motivated. However, such a dataset if available, broadly lack both non-electric information and major appliances measurements comprising ESH and EWH. Finally, introducing a useful dataset becomes more challenging considering uncommon cases like Canadian households with ESH and EWH high energy demand for which, there is no available real-world dataset [13]. In Canada, heating systems set forth a vast utilization of electric baseboards, e.g. Quebec 61% [23] that can significantly confront the HEMS services. Each household is equipped by several electric baseboards which some of them have the same nominal power. Additionally, high switching rate thermostats increase the occurrence of overlapping events. These issues can specifically decrease the performance of NILM techniques and thus, promote the development of a convenient tool for generating related data for further investigations. Accordingly, the main contributions of this study are outlined as below:

1- Generating a semi-synthetic dataset in a sampling period of one second including major electric consumption appliances which enables analyzing specific real-world HEMS cases.

2- Providing a framework capable of creating appealing time-extended load monitoring and control scenarios of different real appliances schedules and non-electric information.

III. Semi-Synthetic Benchmark Development

The proposed approach to generate the semi-synthetic dataset encompasses three important layers which are appliance probabilistic modeling and profile construction, building model simulation, as well as post-processing analysis and on/off power signature generation.

The general model formulation representing the result of the whole data creation system can be expressed by (1) considering the different steps to generate appliances power signatures.

$$y_k = y_k^{esh} + y_k^{ewh} + \sum_{n=1}^{N} y^n w_k^n \tag{1}$$

Where at discrete time k, y_k presents total power consumption; y_k^{esh} describes the heating system power demand which is a function of building thermal factors, environmental parameters, and temperature set-point; y_k^{ewh} stands for the water heater electricity demand which is a function of hot-water consumption, and indoor temperature; and y^n and w^n denote active power value and operation schedule of appliance number n.

In fact, y_k^{esh} and y_k^{ewh} vary by changes in electric appliances usage that affect the household thermal interactions and hot-water consumption, respectively. It is noted that y_k^{ewh} is also a matter of changes caused by household activities e.g. sink and bathroom. This would be another advantage of composing appliances schedules with building models to enable tracking and analyzing of appliances electricity demand specially, ESH and EWH. The description of the general model and its components is presented in the following discussions.

A. *Probabilistic inference of appliances operation schedules*

The energy consumption of household appliances possesses an uncertain pattern due to dynamic behavior of effective factors such as occupants behavior and environmental conditions. Therefore, the operational behavior of loads over time needs to be learned from a stochastic process with no prior knowledge. The reason is that the random processes of the effective factors avoid pre-definition over appliances events during the time of operation. Accordingly, the utilization of a probabilistic modeling to examine the operational activities of power signals is signified. Subsequently, the variables representing the operating features of an appliance are found from probability distributions. The procedure that can be used to discover the appliances schedules is described as follows [24].

1) Appliances time-of-use scheduling: Proposing a distribution over time-of-use of household appliances requires to define time duration in which operational characteristics are likely to have a periodic behavior. In this regard, the time-of-use can be regarded as circular observations from which observed values can be modeled by probability distributions [25]. In fact, the periodic nature of time as a random variable leads to a circular analysis to capture the appliances operation patterns [26]. Therefore, the usage time i.e. the number of time units, t in the period of T, from the initial direction, is specified by an angle, θ given by (2):

$$\Theta = 2\pi \frac{t}{T} \tag{2}$$

The density of an appliance operation during a specific period of time with a circular relationship has the property defined by (3) having a periodic feature as equation (4) [27]:

$$\int_0^T f(\omega)\, d(\omega) = 1 \tag{3}$$

$$f(\omega + T) = f(\omega) \tag{4}$$

The estimation of the uni-variate density $f(x)$ using real-world observations $x_1, ..., x_n$ can be defined by the kernel estimator with kernel k and bandwidth h using (5). This function is modified by employing the von Mises distribution to examine a circular probability density function through (6) [25].

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} k\left(\frac{x - x_i}{h}\right) \tag{5}$$

$$g(\theta; \mu, \kappa) = \frac{1}{2\pi I_0(\kappa)} \exp\{\kappa \cos(\theta - \mu)\} \tag{6}$$

Where the center μ and concentration κ are the mean and variance respectively and I_0 is the modified first kind zero-order Bessel function described by (7).

$$I_0(\kappa) = \frac{1}{2\pi} \int_0^{2\pi} \exp(\kappa \cos(\theta)\, d(\theta)) \tag{7}$$

B. Residential building design

Building Energy Optimization (BEopt) software is a known simulator to model a residential building. This software is promoted by the National Renewable Energy Laboratory (NREL) in order to realize Building America program introduced by U.S. Department of Energy. BEopt prepares the capability of designing single or multi-family buildings with individual characteristics to apply the simulation of different energy consumption scenarios [28]. BEopt employs EnergyPlus engine to process the simulation system. This architecture allows for energy consumption analysis by supplying the related data of indoor/outdoor fundamentals, building thermal interactions, hot water consumption from different sources, and appliance choices and usages [28].

On the other hand, BEopt undergoes two important issues regarding the analysis of total and appliance level electricity use. First, it proposes a deterministic behavior over domestic demands and as a result the consumption schedules are distinct which cannot emulate the real behavior of loads. Furthermore, considering consistent patterns can decline the simulation of real-world scenarios, since a part of ESH and EWH energy demands is defined by heat produced and hot-water amount consumed by relevant appliances, respectively. Secondly, in some cases the appliances from the same type e.g. interior lighting are grouped together and thus, their total energy consumption is simulated which may not be preferable for specific load recognition like individual lighting usages. Therefore, another process is required to generate appliances stochastic power profiles resulted from the probabilistic-based scheduling of real-world data.

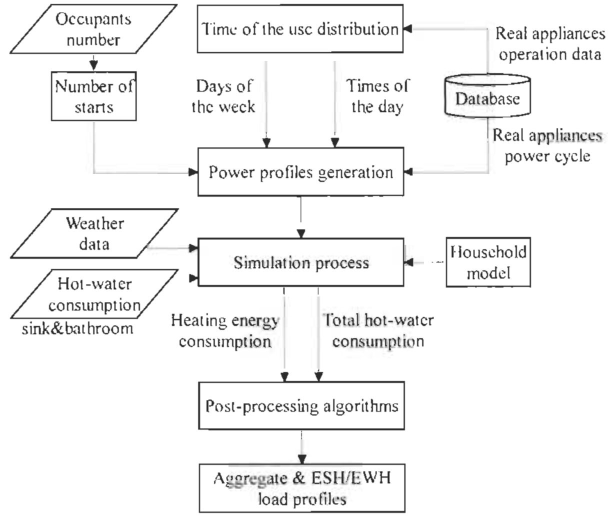

Fig. 1: Definite semi-synthetic data generator structure

C. ESH/EWH power trajectories modeling

In fact, ESH and EWH systems controlled by electronic thermostats, have on/off signal trajectories. However, the related results from building simulator engine do not have such characteristics. Therefore, a post-processing analysis is needed to produce on/off power profiles by tracking the energy consumption of these systems. In order to achieve an actual behavior, the electrical and physical properties of manufactured appliances can be conducted to model well-founded synthetic on/off signals. The proposed procedure of semi-synthetic data generation can be thoroughly summarized in Figure 1.

It is noted that the ability to define hot-water consumption by introducing dynamic schedules of related operations resulted from occupants random activities hands over a realistic approach towards EWH consumption analysis. Subsequently, the hot-water usage can be applied to different manufactured-base models to generate EWH electricity demand.

IV. Result and Discussion

The semi-synthetic data generator benchmark requires two important sets of information in order to execute the simulation

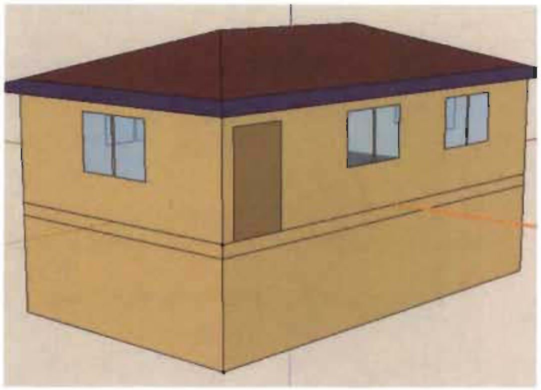

Fig. 2: The sketch of a simple Canadian household modeled by BEopt

TABLE I: The general properties of modeled household

Household specifications
Site location: Trois-Rivieres Weather data: Trois-Rivieres weather condition Size: 700 sqft Number of zones: Two including living and basement zones Wall thermal resistance: Wood Stud, R23 (closed cell spray foam) Number of windows: Six with total area of 132 sqft

process. This information encompasses environmental conditions and building characteristics as well as desired appliances active-power values and operation schedules. Accordingly, the environmental information of Trois-Rivières city located in Quebec, Canada where this study is conducted, has been introduced to the simulation system [29]. Moreover, a simple household has been modeled using BEopt software, considering the general properties of an average Canadian home [30]. The specification of the modeled house is summarized in Table I. It is noted that detailed construction material modeling is out of the scope of this study. A schematic sketch of the house is shown in Figure 2.

On the other side, the statistical analysis has been applied to real-world data from ECO database, [9] in order to give a practical viewpoint to electrical appliances energy demand in the house and catch their actual stochastic behavior. As a result, the operation schedules of electrical appliances have been estimated using the probabilistic models of their daily and weekly usages. Finally, the time-extended non-deterministic time-series of appliances power profiles in one-second sampling frequency have been created using their operations probabilistic distributions and real power signatures. The targeted appliances for statistical analysis consist of refrigerator, stove, and dishwasher located in zone 1, as well as washing-machine and dryer located in zone 2 which is a common style in the houses with basement area. The daily/weekly operation schedules of these appliances are illustrated in Figures 3 and 4, respectively. As it can be seen, the refrigerator weekly/daily schedules are likely uniformed distributions due to periodicity

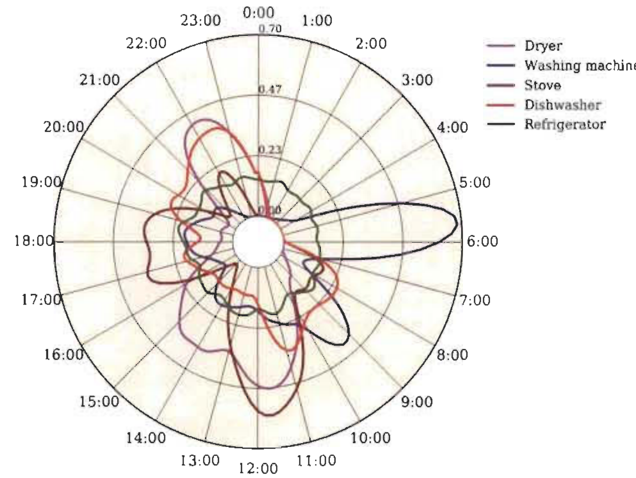

Fig. 3: Daily probabilistic operation of targeted appliances

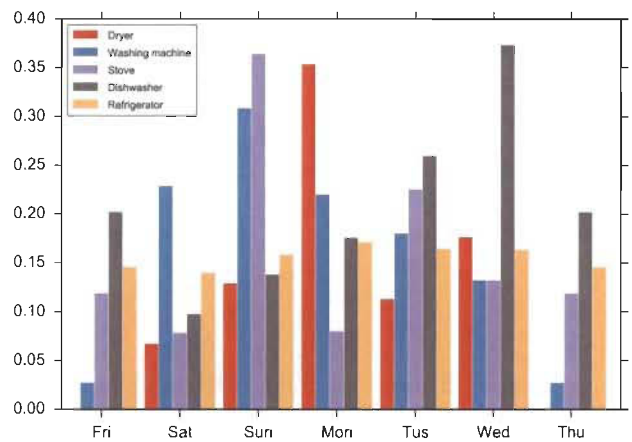

Fig. 4: Weekly probabilistic operation of targeted appliances

in duration statistics of an actual domestic refrigerator. It should be noted that these appliances along with EWH and ESH account for more than 90% of a typical Canadian household electric energy consumption [31].

Subsequently, the provided information have been given to the building simulator to examine the heating system electricity demand and hot-water usage in the modeled house. Afterward, ESH and EWH on/off profiles have been generated through a post-processing step executed using the data resulted from simulated demands.

In this regard, based on a water heater model proposed in [32] EWH time-extended power profile has been constructed. The proposed EWH [with nominal values 3kW at 240V] has 2.8kW power use corresponding to 232V which has been located in zone 2. Figure 5 shows the results for a period of one day. As it can be seen, the on/off EWH load profile demonstrates a higher rate of activities which demand hot water, in the afternoon for the related day. Such analyses through scheduling the occupants different energy consump-

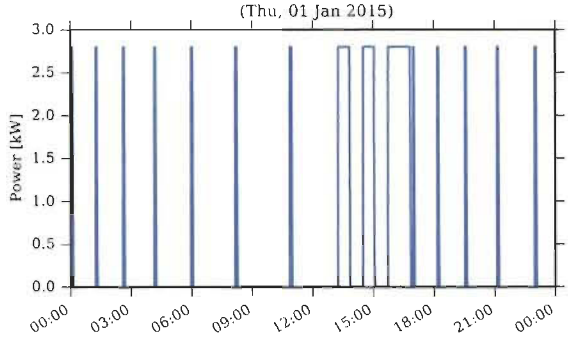

Fig. 5: EWH on/off power profile for one-day time duration

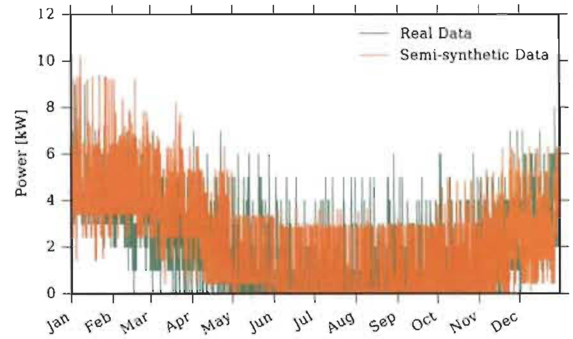

Fig. 7: Yearly semi-synthetic aggregated and real-wold measured power profiles

tion patterns can benefit demand side management strategies.

In addition, heating energy consumption has been distributed among seven 1kW baseboards in zone 1 and three 500W baseboards in zone 2 in a way that none of them indicates the same behavior. The model used to generate ESH on/off power profiles has been developed based on electrical characteristics of an electronic thermostat. This thermostat operates based on a PWM technique with a time period of 16 seconds. A Gaussian noise, ξ drawn from (8) is added to the signal to capture more actual aspect. The mean μ, and variance σ^2, have different values in on and off events based on our measurements of several electric baseboards on/off states.

$$\xi \sim \mathcal{N}\left(\mu, \sigma^2\right) \tag{8}$$

Figure 6 presents the generated load profile of a 1kW electric baseboard in around half-an-hour. As it is shown, the created signal using the proposed model manifests high event rates variations with saturation times. These are of the main behavior of electric baseboards operation periods particularly, in cold climates.

Subsequently, semi-synthetic aggregated power profile is created based on (1) using real and synthetic appliances power profiles. Figure 7 illustrates the long-term generated results and real-world measured data of a Canadian case from [33] with an hourly sampling interval. It can be realized that the semi-synthetic data has the same trend and behavior as well as similar total power demand as the real data. Furthermore, the impacts of ESH and EWH power trajectories on the aggregated power signal is demonstrated in Figure 8. This figure presents daily load profiles of generated data and house 1 in ECO database. As it can be seen, the high event rates of several ESH which some of them have the same power demand, and short duration operations of EWH can lead to a complicated aggregated signal for HEMS services analyses. This signal includes a high number of overlapping events which makes it a difficult case for NILM.

Finally, the generated data can be regarded as a household fundamental electricity signal which consists of appliances that their long-time consumption exhibit relationship with occupants behavior, thermal interactions, and environmental conditions. The dataset development tool is specially beneficial for NILM time-extended studies since it accounts for necessary information. In addition, by introducing the appliances schedules drawn from publicly available real-world data of Canadian houses, this structure can capture a more practical perspective of such exceptional cases concerning the analysis of different HEMS scenarios. It should be mentioned that the ability of this tool to generate data can give the possibility for further studies in the context of an advanced HEMS.

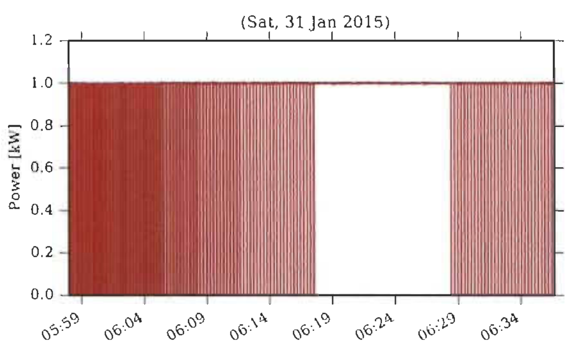

Fig. 6: On/off power profile of a 1kW ESH for half-an-hour time duration

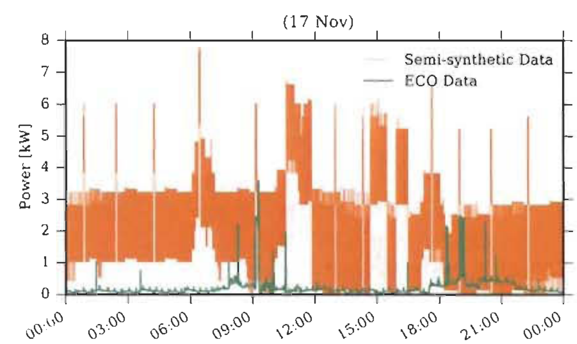

Fig. 8: One-day aggregated power profiles of semi-synthetic dataset and house 1 in ECO database

V. Conclusion and Future Work

The Canadian households major electric consumption appliances along with long cold seasons bring about specific complicated energy management cases. Such situation requires an appropriate dataset for HEMS studies that enables a time-expanded analysis of major appliances including ESH and EWH. Due to difficulties related to defining a real-world available database addressing these issues, we have developed a tool to generate time-specific semi-synthetic data. The constructed dataset which has a one-second sampling rate provides the electric information of EWH and ESH appliances as major usages vital for energy consumption analyses relevant to our case. Moreover, this dataset includes both second-level major domestic loads and non-electric data over a long time. As a result, the dataset development tool can also benefit industrial applications for which it is necessary to study the relationship between occupants behavior and temperature fluctuations with electricity consumption patterns. In our future work, this dataset will be specially used for NILM practice in different cases i.e. major appliances, time-expanded, and non-electric information analysis.

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References

[1] D. Alahakoon and X. Yu, "Smart Electricity Meter Data Intelligence for Future Energy Systems: A Survey," *IEEE Transactions on Industrial Informatics*, vol. 12, no. 1, pp. 425–436, 2 2016.

[2] Q. Hu, F. Li, and C.-f. Chen, "A Smart Home Test Bed for Undergraduate Education to Bridge the Curriculum Gap From Traditional Power Systems to Modernized Smart Grids," *IEEE Transactions on Education*, vol. 58, no. 1, pp. 32–38, 2 2015.

[3] J. Paris, J. Donnal, Z. Remscrim, C. Schantz, J. L. Kirtley, S. B. Leeb, U. A. Orji, M. Gillman, and K. Surakitbovorn, "Non-intrusive induction motor speed detection," *IET Electric Power Applications*, vol. 9, no. 5, pp. 388–396, 5 2015.

[4] M. Zeifman and K. Roth, "Nonintrusive appliance load monitoring: Review and outlook," *IEEE Transactions on Consumer Electronics*, vol. 57, no. 1, pp. 76–84, 2 2011.

[5] P. Gao, S. Lin, and W. Xu, "A Novel Current Sensor for Home Energy Use Monitoring," *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 2021–2028, 7 2014.

[6] D. Zufferey, C. Gisler, Omar Abou Khaled, and J. Hennebert, "Machine learning approaches for electric appliance classification," in *2012 11th International Conference on Information Science, Signal Processing and their Applications (ISSPA)*. IEEE, 7 2012, pp. 740–745.

[7] L. Yang, X. Chen, J. Zhang, and H. V. Poor, "Cost-Effective and Privacy-Preserving Energy Management for Smart Meters," *IEEE Transactions on Smart Grid*, vol. 6, no. 1, pp. 486–495, 1 2015.

[8] A. Ridi, C. Gisler, and J. Hennebert, "Automatic identification of electrical appliances using smart plugs," in *2013 8th International Workshop on Systems, Signal Processing and their Applications (WoSSPA)*. IEEE, 5 2013, pp. 301–305.

[9] C. Beckel, W. Kleiminger, R. Cicchetti, T. Staake, and S. Santini, "The ECO data set and the performance of non-intrusive load monitoring algorithms," in *Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings - BuildSys '14*. New York, New York, USA: ACM Press, 2014, pp. 80–89.

[10] R. Bonfigli, S. Squartini, M. Fagiani, and F. Piazza, "Unsupervised algorithms for non-intrusive load monitoring: An up-to-date overview," in *2015 IEEE 15th International Conference on Environment and Electrical Engineering (EEEIC)*. IEEE, 6 2015, pp. 1175–1180.

[11] Y.-H. Lin and M.-S. Tsai, "An Advanced Home Energy Management System Facilitated by Nonintrusive Load Monitoring With Automated Multiobjective Power Scheduling," *IEEE Transactions on Smart Grid*, vol. 6, no. 4, pp. 1839–1851, 7 2015.

[12] Oliver Parson, "Disaggregated Homes: Public Data Sets for NIALM," 2016. [Online]. Available: http://blog.oliverparson.co.uk/2012/06/public-data-sets-for-nialm.html

[13] Natural Resources Canada, "Energy Efficiency Trends in Canada 1990 to 2009," Tech. Rep., 2011. [Online]. Available: http://oee.nrcan.gc.ca/publications/statistics/trends11/pdf/trends.pdf

[14] D. Egarter, V. P. Bhuvana, and W. Elmenreich, "PALDi: Online Load Disaggregation via Particle Filtering," *IEEE Transactions on Instrumentation and Measurement*, vol. 64, no. 2, pp. 467–477, 2 2015.

[15] H. Pihala, "Non-intrusive appliance load monitoring system based on a modern kWh-meter," TECHNICAL RESEARCH CENTRE OF FINLAND, Espoo, Tech. Rep., 1998. [Online]. Available: http://www.vtt.fi/inf/pdf/publications/1998/P356.pdf

[16] K. Carrie Armel, A. Gupta, G. Shrimali, and A. Albert, "Is disaggregation the holy grail of energy efficiency? The case of electricity," *Energy Policy*, vol. 52, pp. 213–234, 1 2013.

[17] A. Zoha, A. Gluhak, M. Imran, and S. Rajasegarar, "Non-Intrusive Load Monitoring Approaches for Disaggregated Energy Sensing: A Survey," *Sensors*, vol. 12, no. 12, pp. 16 838–16 866, 12 2012.

[18] Y.-H. Lin and M.-S. Tsai, "Non-Intrusive Load Monitoring by Novel Neuro-Fuzzy Classification Considering Uncertainties," *IEEE Transactions on Smart Grid*, vol. 5, no. 5, pp. 2376–2384, 9 2014.

[19] S. Sathiracheewin and V. Surapatana, "Daily typical load clustering of residential customers," in *The 8th Electrical Engineering/ Electronics, Computer, Telecommunications and Information Technology (ECTI) Association of Thailand - Conference 2011*. IEEE, 5 2011, pp. 797–800.

[20] K. Anderson, A. F. Ocneanu, D. Benitez, D. Carlson, A. Rowe, and M. Bergés, "BLUED : A Fully Labeled Public Dataset for Event-Based Non-Intrusive Load Monitoring Research," *Proceedings of the 2nd KDD Workshop on Data Mining Applications in Sustainability (SustKDD)*, no. October 2011, pp. 1 – 5, 2012.

[21] A. S. Uttama Nambi, A. Reyes Lua, and V. R. Prasad, "LocED: Location-aware Energy Disaggregation Framework," in *Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments - BuildSys '15*. New York, New York, USA: ACM Press, 2015, pp. 45–54.

[22] J. Z. Kolter and M. J. Johnson, "REDD : A Public Data Set for Energy Disaggregation Research," *SustKDD workshop*, vol. xxxxx, no. 1, pp. 1–6, 2011.

[23] Statistics Canada, "Households and the Environment: Energy Use Analysis," 2007. [Online]. Available: http://www.statcan.gc.ca/pub/11-526-s/2010001/part-partie1-eng.htm

[24] B. Stephen, S. Galloway, and G. Burt, "Self-Learning Load Characteristic Models for Smart Appliances," *IEEE Transactions on Smart Grid*, vol. 5, no. 5, pp. 2432–2439, 9 2014.

[25] N. I. Fisher, *Statistical Analysis of Circular Data*. Cambridge: Cambridge University Press, 1993.

[26] K. V. Mardia and P. E. Jupp, *Directional Statistics*. Chichester, U.K.: Wiley, 2000.

[27] H. Xu and F. P. Schoenberg, "Kernel regression of directional data with application to wind and wildfire data in Los Angeles County, California," 2007. [Online]. Available: http://www.stat.ucla.edu/~frederic/papers/winddir106.pdf

[28] National Renewable Energy Laboratory (NREL), "BEopt Version 2.7: New Features," 2016. [Online]. Available: https://beopt.nrel.gov/sites/beopt.nrel.gov/files/exes/Features.pdf

[29] Hydro Quebec, "SIMEB - Simulation énergétique des bâtiments." [Online]. Available: https://www.simeb.ca/index.php?/Core/Default/Index

[30] National Post, "The incredible shrinking home: Why Canadas houses are getting smaller." [Online]. Available: http://news.nationalpost.com/news/canada/the-incredible-shrinking-home-why-canadas-houses-are-getting-smaller

[31] Natural Resources Canada, "Water Heater Guide," Tech. Rep., 2012. [Online]. Available: http://www.nrcan.gc.ca

[32] Z. Xu, R. Diao, S. Lu, J. Lian, and Y. Zhang, "Modeling of Electric Water Heaters for Demand Response: A Baseline PDE Model," *IEEE Transactions on Smart Grid*, vol. 5, no. 5, pp. 2203–2210, 9 2014.

[33] Hydro Quebec, "Meeb : Maisons dexpérimentation en énergétique du bâtiment." [Online]. Available: https://meeb.ca/fr/

3.3 Household database construction approach

3.3.1 Background

Although NILM is a traditional subject, thoroughly studied for many years, the ambition to investigate its diagnosis capability has been overlooked. Diagnosis services can be regarded as a key facility of advanced ALM systems. Therefore, the examination of the requirements of a diagnosis system in the context of NILM can be innovative. This idea can bring about enhanced insights into NILM main processes of appliances' load model learning, disaggregation, and identification. Accordingly, the second study has its roots in designing a NILM system for diagnosis purposes. The development of such a system needs an extensive framework with different procedures that are not limited to only a load disaggregation phase. The essence of this framework aims a process with an explicit intention of constructing valid appliance models and providing a flexible mechanism that is not restricted to the static models. This architecture is characterized to realize a systematic model-discovery scheme that is able to detect new events as they occur and start their detection with routine information. Furthermore, such an enhanced structure necessitates the development of an adaptable procedure to recognize the operation trends of existing models for their parameters' update. Correspondingly, our ambition to achieve the aforementioned framework has resulted in the approach of household appliances' database construction that is formulated based on an adaptive on-line unsupervised method.

3.3.2 Methodology

The proposed mechanism for household database creation is realized through a set of algorithms that can ultimately uncover underlying load models with robust parameters from the household aggregated signal as the only source of information. Therefore, the uncovered load models are dealt with as Virtual Appliances (VA) because of the lack of any prior knowledge. This mechanism is based on an adaptable method as the key answer to a gradually model generation concept [101]. Moreover, unsupervised machine-learning algorithms that use no labeled data to recognize and update the models are employed, which rise the importance of an adaptive means [102]. The above architecture is executed by an Appliance Database

Constructor (ADC). Our ADC has a dynamic characteristic, since the load models, which are stored in the database, evolve over time. ADC carries out the following steps to complete the entire procedure of Figure 3-2.

- Model detection and supervision: This step applies a pattern recognition procedure for both detecting likely VA, which have not been previously modeled, as well as supervising current VA, stored in the database. This procedure takes advantage of subtractive clustering and KDE methods.

- Model construction and revision: Designed with an on-line model learning technique, this phase consists of low-complexity algorithms that result in both constructing new VA and revising the existing ones. The modeling process utilizes an HMM with dynamic parameters that is updated by using a Viterbi Training (VT) algorithm.

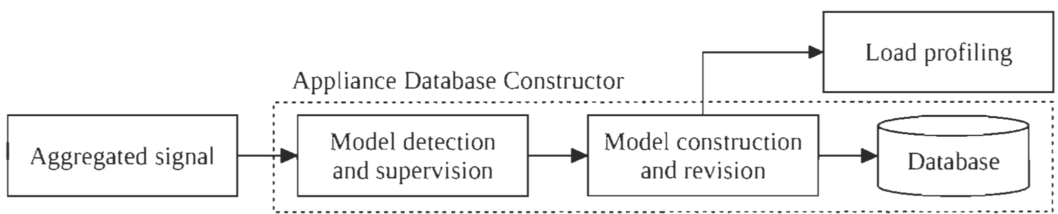

Figure 3-2 Block diagram of ADC in accordance with the proposed approach of household database construction.

3.3.3 Outcomes

The investigation into a NILM for diagnosis purposes and the household database construction approach has provided new understandings of an appliance-level load monitoring system. To be precise, these comprehensions have been made based on the examination of ADC within its specific contexts, explained below.

- Resulting models: The electrical features of constructed VA as the final results of the modeling process have been evaluated. VA can be identified by using their features and general information of household appliances.

- ADC steps: ADC consists of different procedures, which require their own analysis. Accordingly, model detection and construction as the main steps of ADC have been analyzed. Furthermore, two important processes of pattern recognition and load profiling, described in the article have been discussed.

- Simulation process: Due to the adaptive nature of the proposed algorithm, not only the results, but also the process evolution has been elucidated in order to provide an actual evaluation. Furthermore, the structure of the designed database has been represented in order to detail its management by ADC within the process. Additionally, the capability of the adaptable procedure to capture the dynamic of the consumption and improve the estimated parameters of VA has been discussed.

The following study demonstrates the results of the household appliance database construction approach through an extensive analysis.

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Adaptive on-line unsupervised appliance modeling for autonomous household database construction

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ABSTRACT

Enabling diagnosis capabilities of Appliance Load Monitoring (ALM) necessitates providing in-operation information of appliances' behavior. Due to both appliances' time-varying model parameters and operations, household aggregated consumption has a dynamic structure. Existing time-invariant load models, built of off-line datasets with static information, are not sufficient to capture the actual behavior of the power consumption. In fact, these models, generally obtained from exhaustive training phases are intended to satisfy load monitoring goals. Therefore, a time-variant load modeling is more practical to capture such a dynamic property of the power consumption. Accordingly, this paper presents an adaptive on-line appliance-level load modeling approach, to design a load monitoring structure for diagnosis purposes. By using the aggregated power consumption of individual households, our proposed structure results in an autonomous household database construction. The modeling procedure begins with a designed recurrent pattern recognition system that is capable of detecting and maintaining load models. This load model structure is determined by using a hidden Markov model (HMM) with dynamic parameters, that are extracted from aggregated signal and trained within an on-line learning process. Our proposed approach can detect time-varying power consumption behavior and estimate the robust load models of appliances. Additionally, our novelty in employing a set of straightforward algorithms, suggests the practicality of our database construction approach.

1. Introduction

Appliance Load Monitoring (ALM) is an applicable foundation for load diagnosis services to recognize statistical deviations in load consumption behavior [1]. In this regard, ALM, which is a prerequisite of load diagnosis estimation algorithms, needs a framework capable of providing in-operation information of appliances [2]. Such information can be provided through continuously monitoring household appliances' power consumption and capturing their behavior.

1.1. Household ALM context

An ALM approach that uses the data from a single metering point is known in the literature as Non-Intrusive Load Monitoring (NILM) [3]. In the context of NILM, the goal is the disaggregation of appliances' power consumption trajectories from the aggregated signal [4]. In NILM, the efficient methods mainly utilize previously learned models of known appliances' load, which are captured through an extensive training phase [5–8]. In fact, by using off-line datasets with static information, they construct time-invariant load models to satisfy load-monitoring goals through generally an off-line load disaggregation. The resulting load models with fixed parameters provide an invariable examination of appliances' behavior [9–11]. Therefore, they are not practical enough to realize the actual behavior of the power consumption. The aforementioned restrictions of NILM has caused its diagnosis potential to be overlooked.

1.2. Contribution

This paper aims to design an ALM system for load diagnosis purposes in a non-intrusive context. Both time-varying model parameters and operations of household appliances, give the aggregated power consumption a dynamic structure. As a result, a time-variant appliance-level load modeling framework is more practical to capture such a

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Nomenclature

w	time window index (data frame cell index)
ζ	constant adaptation coefficient
ϵ	positive constant
μ, σ^2	mean, and variance parameters of Gaussian distribution function
$f'(.)$	Gaussian distribution function
π	state distribution vector
A	transition matrix
B	emission matrix
C_v	v^{th} cluster center
$f(.)$	Marginal Probability Density Function (PDF)
$\hat{f}(.)$	Kernel Density Estimation (KDE) function
h	bandwidth parameter of Kernel function
$\mathscr{K}(.)$	Kernel function
N	number of observations at time window w
$\mathbf{x}_w$	set of observations at time window w
$\Delta\mathbf{x}_w$	set of absolute value of Δy_k at time window w
y_k	observation at discrete time k
Δy_k	consecutive observations difference at discrete time k

dynamic property of the power consumption. This modeling framework can allow the recognition of new presenting loads and gradual changes in existing ones in the aggregated signal. Accordingly, we present an adaptive on-line unsupervised approach to perform a time-variant appliance-level load modeling as a prerequisite for a load monitoring system with diagnosis goals. The proposed approach results in an autonomous household database construction to explore time-varying behavior of the power consumption.

The details of our proposed approach can be presented in terms of: (1) a flexible load modeling framework, designed by a set of straightforward algorithms, that uses 1 Hz sampled data of aggregated power consumption; (2) a recurrent pattern recognition process that is able to detect and maintain probable load models; (3) an adaptable procedure that is capable of realizing an on-line load model learning mechanism; (4) a HMM representation of appliances' load with dynamic parameters, which is initialized using a non-parametric method, combined with a parametric mixture model; (5) a load model construction of major appliances with high accuracy, which is employed for a fully unsupervised load profiling phase. From this perspective, we treat an uncovered load (that may present an actual appliance) as a Virtual Appliance (VA).

The rest of the paper is organized as follows. Section 2 provides a review of recent studies on appliance load modeling in the context of NILM. Section 3 describes the proposed approach methodology through an in-depth discussion. Section 4 presents the evaluation framework of the developed method. Section 5 examines the method performance by presenting the results of different tests on public and experimental data, that is followed by a discussion in Section 6. The concluding remarks are presented in Section 7.

2. Background

NILM approach has been proposed as an alternative to the burdensome intrusive ALM approaches [5,12–14]. Hart [3] is the first to study NILM. Subsequently, many research studies have used this approach to recognize a set of household appliances in the aggregated signal through load disaggregation method. They have investigated this method based on either a steady-state analysis of low-sampling rates of electric load signals or a transient analysis of high-frequency ones [15–17]. However, due to smart meter capabilities to provide low-sampling rate data (regarding their real-world deployment issues), the former has been mostly into consideration [18]. To be precise, due to their energy saving potentials, the researches have usually targeted appliances with costly power consumption through a steady-state analysis [6,9,19,20].

Load disaggregation have been examined by employing many machine learning algorithms [21–24]. Former methods, which have been usually used for load disaggregation, consist of Artificial Neural Networks (ANN) [25,26], Support Vector Machines (SVM) [27,28], k-Nearest Neighbor (k-NN) algorithms [29,30], and Decision Tree (DT) [31,32]. These learning algorithms can face different difficulties. For example, ANN are simple, but at the cost of an arbitrary development (of construction and training phases). SVM and k-NN can be computationally expensive. Instability problems in the presence of perturbations in the data can challenge DT [9,33]. Moreover, recent achievements of Deep Learning (DL) methods in data processing have caused their utilization for NILM [34–37]. Although DL models can be very efficient, the need for a huge amount of data to train a large parameter space and a heavy processing power to manage an expensive computational complexity can affect their efficiency [38].

Besides, state-based approaches, particularly Hidden Markov Models (HMM) have been the state-of-art method for load disaggregation. Due to their capability to provide analytical state-based models of household appliances, the variants of HMM have become the main focus of most researches [39–41]. They can effectively explain the aggregated signal as the combination of operation sequences of individual appliances [11]. In fact, the essence of HMM is qualified to model time-series of appliances' load and interpret their actual behavior. Generally, the studies based on HMM have utilized the labeled data from an available dataset in order to build a set of load models of targeted appliances. Accordingly, they have developed either supervised or semi-supervised learning methods. In the former method, the exclusive load models have been tested on unseen instances from the same dataset as training. For example, the PALDi method, proposed by Egarter et al. [19], has recommended a training-free load disaggregation by using Factorial HMM (FHMM), which has been constructed from appliances' sub-metered measurements. Likewise, Kong et al. [6] have built FHMM of appliances however, through a considerably lengthy training phase compared to Egarter. Furthermore, they have evaluated their method by applying an optimization algorithm with a costly computation time. Makonin et al. [9] have aimed to evade HMM complicated types, while preserving its performance, by using a super-state HMM. However, their model builder demands a valid prior-data of targeted appliances in order to realize an efficient training phase. Consequently, their approach to collect the labeled data and evaluate the models' efficiency offers an intrusive mechanism. Generally, the main issue with supervised techniques is their generalization ability. In the latter method, the generic load models have been tuned to specific appliances' load in other datasets. For instance, Parson [7] has exploited a difference FHMM to create generic load models by using the prior data of an available dataset. Subsequently, he has trained these models to exclusive load models. The scalability of the algorithm is usually the main challenge of semi-supervised methods. Indeed, the common facet of the above studies is the utilization of a learning phase, that mainly requires an off-line run to train load models.

In addition, the researchers have employed different HMM variants to study load disaggregation through unsupervised learning methods. By avoiding labeled data of an available dataset, they have created appliances' load models by using a set of priors, mostly based on their general information. However, these methods have not been much into consideration. For instance, Hart [3] has extended a thorough unsupervised disaggregation algorithm to build appliances' load models. However, his technique suffers from a deterministic load modeling structure, which does not capture a real-world scenario. Kim et al. [42] has proposed a learning process consisting of four different FHMM.

However, the real-time configuration of a computationally expensive mechanism, the complex structure of several FHMM, and the initialization and assumptions of model parameters are the main issues of their suggested procedure. Johnson and Willsky [43] have exploited Hidden Semi-Markov Models (HSMM). Although they have stated that their efficient method can account for an unsupervised learning, they have utilized the same dataset for both building the models and reporting the results. Guo et al. [44] have developed an Explicit-Duration HMM (EDHMM) with differential observation for load modeling. They have set up their learning process by appliances' general information. Notwithstanding, their work lacks addressing the method application for load disaggregation, and evaluating fairly the proposed modeling process. More detailed review of load disaggregation algorithms have been conducted in [45]. Furthermore, we have investigated essential prerequisite of a successful NILM system in [1].

Due to complicated task of load disaggregation, it has become the main goal of NILM. Therefore, a comprehensive investigation of the essential prerequisites for enabling the diagnosis capacity of a NILM has been ignored.

3. Appliance database construction methodology

3.1. Automatic arrangement of aggregated data

The database construction procedure is applied to the aggregated signal, which is automatically organized in an on-line framework by using the data arrival time. In this regard, a data frame is constructed, in which the total signal is collected as a time-series, indexed in a date-time basis with one second intervals. Subsequently, the data frame is tabulated in a way that the number of observations in each cell correspond to the duration of time window. Regarding the operation cycle of household appliances, this time window is considered to be one hour. In fact, each cell of tabular data (which is related to an individual time window) should comprise sufficient data points to provide meaningful information for load modeling. Now with a tabulated data structure, the constructed data frame can enable the evaluation of the collected data in terms of a sequential analysis. To further clarify the data frame, we should note that the table is set to hold the information of one day; meaning we have a table of 24 cells (each for one time window). Therefore, let $w \in \{1, 2, ..., 24\}$ be the index of each time window that encompasses one hour of power data measurements, denoted by y_k, where k is the discrete time index. Consequently, the subset of power readings related to each w can be defined as $\mathbf{x}_w = \{y_k | k = (w-1)N + 1 ... wN\}$, where $N = 3600$ is the number of observations in the time window. From the data in $\mathbf{x}_w$, $\Delta\mathbf{x}_w$ is constructed, which is the subset of absolute values of the difference between each two consecutive observations, given by $\Delta\mathbf{x}_w = \{|\Delta y_k| | \Delta y_k = y_k - y_{k-1}, y_k \in \mathbf{x}_w\}$. Afterwards, our proposed methodology is applied to the positive differential observations (Pdiff) in $\Delta\mathbf{x}_w$. In fact, we consider a common assumption for load modeling, that is at most one appliance changes its state during a short sampling interval [44]. As a result, we can analyze differential observations in order to capture the power consumption of unknown appliances' load, since we have no prior knowledge about them.

3.2. Appliance database constructor

The proposed mechanism for household database construction can ultimately uncover the underlying VAs with robust parameters from the aggregated signal. This mechanism is based on an adaptive process, which assists with a gradual model generation procedure through employing an unsupervised machine-learning algorithm [46,47]. To do so, we develop an extensive adaptable system that is executed by an Appliance Database Constructor (ADC). Our ADC has a dynamic characteristic, since the load models, which are stored in the database, evolve over time. ADC carries out the following steps to complete the entire procedure of Fig. 1. As mentioned, due to the lack of any prior knowledge, uncovered load models are dealt with as VAs.

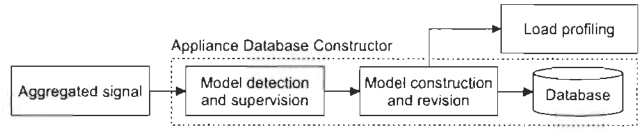

Fig. 1. Block diagram of our appliance database constructor in accordance with the proposed approach of household database construction.

1- Model Detection and Supervision: This step applies a pattern recognition procedure for both detecting likely VAs, which have not been previously modeled, as well as supervising current VAs, stored in the database (explained in Section 3.2.1).
2- Model Construction and Revision: Designed with an on-line model learning technique, this phase consists of low-complexity algorithms that result in both constructing new VAs and revising the existing ones (explained in Section 3.2.2).

ADC continuously monitors the database in order to properly operate the above steps (explained in Section 3.2.3). Concurrently with every step, it manages the database in order to add and update VAs. In the database, VAs are labeled by two elements, their power consumption patterns and time window index of their first occurrence. Furthermore, their model is structured by HMM parameters (discussed in detail below). In addition, we develop an unsupervised load profiling technique by using VAs, created by ADC (explained in Section 3.3). In what follows, the adaptive on-line process of model detection, construction, and revision of VAs during a time window is described.

3.2.1. Model detection and supervision

ADC begins this step with a pattern recognition process. It employs Kernel Density Estimation (KDE) method in order to recognize the power consumption patterns in the aggregated signal. KDE is a simple non-parametric method and thus, a perfect fit for the density estimation of data streams with unknown underlying distribution. Therefore, it can benefit our unsupervised load modeling technique, which uses no prior knowledge [48]. Particularly, we apply a Gaussian-based KDE function to Pdiff in order to detect power consumption patterns by exploring their density variations. This function can be formulated as (1),

$$\hat{f}(x) = \frac{1}{N-1} \sum_{j=1}^{N-1} \mathscr{K}_h(x - \Delta y_j) \tag{1}$$

where x specifies the discrete support. $\hat{f}(.)$ presents KDE function with Gaussian kernel, $\mathscr{K}(.)$, centered at Δy_j. h is the bandwidth parameter with an empirically chosen value of 15 for all the process. We have employed Gaussian function in our analysis, since it is capable of providing an acceptable model of finite-state load appliances (such as fridge, stove, and dishwasher), regarding their steady-state operation [42]. Furthermore, in order to avoid complexity, we have considered a constant bandwidth parameter that has resulted in a better estimation through our experiments. Moreover, in order to detect the recurrence of patterns within time windows, an adaptive detection scheme is used. This scheme results in a discrete distribution as marginal *Probability Density Function* (PDF) of power consumption. In each time window, the adaptive scheme revises this distribution by a portion of the difference between KDE and its previous estimate. This, in turn, forms a non-parametric recursive distribution, described by (2) [49],

$$f_w(x) = f_{w-1}(x) + \zeta(\hat{f}_w(x) - f_{w-1}(x)) \tag{2}$$

that $f_w(x)$ and $f_{w-1}(x)$ present the discrete distribution and its previous estimation. ζ is the constant adaptation coefficient that is considered 0.1 for all the process. This coefficient has been experimentally selected from a numerical range of [0, 1]. Due to the stochastic nature of aggregated signal, the primary PDF is defined as a uniform distribution to avoid any prior assumption. The resulting PDF consists of regions with higher emission probability that determine the power consumption patterns. ADC examines these patterns to construct the database of VAs (the start of the modeling process). More importantly, the adaptive scheme recognizes the recurrence of patterns by detecting their trends based on their density variations within time windows. Furthermore, these variations are used to identify the operation state of their related VAs, which signifies the advantage of our process for diagnosis systems. Indeed, the emission distribution of an appliance in the aggregated signal can be decreased to lower probability in the presence of other appliances, noise, and notable transients [44]. Our tests demonstrate that the adaptive scheme avoids the loss of patterns in such situations (discussed more in Section 5) [49].

In fact, not all the patterns, detected in $f_w(x)$ belong to appliances' loads. Therefore, patterns that present probable VAs need to be identified. We describe them as Patterns of Interest (PoI) and utilize a peak detection phase to extract them. This phase searches for patterns with probabilities higher than a threshold and extracts them consecutively. Our peak detection method takes advantage of Subtractive Clustering algorithm. This algorithm is appropriate for our analysis, since it is an unsupervised clustering method, which requires no predefined cluster numbers. Subtractive clustering (until verifying the termination criterion) iteratively (i) catches the cluster with highest probability through (3), and (ii) revises the probability distribution through (4),

$$C_v = \underset{x \in \{x_1, x_2, \ldots, x_N\}}{\arg\max} \; (p_{ite}(x)) \tag{3}$$

$$p_{ite+1}(x) = p_{ite}(x) - \acute{p}(C_v)\exp\left(-\frac{1}{2}\left(\frac{x - C_v}{\acute{h}}\right)^2\right) \tag{4}$$

where *ite* is the iteration and $p_1(x)$ is equal to $f_w(x)$, because we need to maintain the form of $f_w(x)$ for evaluating the recurrence of the patterns. C_v is the chosen cluster with index number v and probability value $\acute{p}$. The constant radius $\acute{h}$ is set to $1.5h$ in order to efficiently make potential neighbors as unlikely cluster centers. The iterations terminate when $\acute{p}(C_v) < \epsilon \acute{p}(C_1)$, where ϵ is a positive constant. As a result, this algorithm creates a class of cluster centers (power values) that present PoI.

The model detection and supervision step results in a set of PoI at every time window of analysis. PoI consist of both new and recurrent patterns. We utilize a likelihood estimation to differentiate between these two, by using the patterns that have been previously stored. Consequently, our adaptive on-line process applies the following updates to the database. New patterns and the time window index of their occurrence (only the first occurrence) create new labels, while recurrent ones revise previous labels. The type of patterns (new or recurrent) defines the successive modeling processes. Accordingly, new patterns, which can be described as VAs, are modeled through model construction phase. In addition, recurrent patterns, which their relevant VAs have been previously stored, are updated through model revision phase. ADC also handles these phases in an adaptive manner.

3.2.2. Model construction and revision

In this section, we describe the construction and revision of a single VA. In model construction step, new PoI are modeled as VAs by extracting their model parameters directly from the aggregated signal. In fact, each new PoI can present a VA. As mentioned, aggregated signal can be expressed as a non-Gaussian distribution of Gaussian mixture models of finite-state load appliances. Indeed, these appliances account for a major part of total power consumption. Therefore, the power consumption of a VA is assumed to have a Gaussian distribution. The parameters of this Gaussian are initialized by using new pattern's value, C as mean and bandwidth, h as variance. Consequently, we classify Pdiff in $\Delta\mathbf{x}_w$ according to initial Gaussian parameters by utilizing Inverse Normal Distribution function, defined by (5)

$$\mathbf{y} = \{\Delta y_k | \mu - \delta\sigma \leqslant \Delta y_k \leqslant \mu + \delta\sigma\} \tag{5}$$

where μ and σ present the mean and standard deviation parameters of a VA's Gaussian distribution. δ is equal to 3 based on three-sigma rule of thumb. $\mathbf{y}$ comprises the set of Δy_k, classified under new Gaussian component. Subsequently, the mean and variance parameters of this component are re-estimated by using its relevant power values in $\mathbf{y}$. In fact, the primary parameters of new Gaussian are used to detect its relevant Pdiff in the time window, since they are more precise to estimate its mean and variance (regarding our unsupervised method). As a result, by using a new PoI's value, a Gaussian distribution that presents a VA power consumption is constructed. Afterwards, the model construction of a VA is achieved by employing its Gaussian parameters.

In fact, a VA in the database is presented as a difference HMM [50], which is determined by a set of parameters $\lambda = (\pi, A, B)$ that: for Z number of states and $1 \leqslant i,j \leqslant Z$, $\pi = \{\pi_i\}_{Z\times 1}$ is the state distribution vector, where $\pi_i = P[q_1 = i]$, P is the probability, and q_k is the state at k, $A = \{a_{ij}\}_{Z\times Z}$ is the transition matrix, where $a_{ij} = P[q_k = j | q_{k-1} = i]$, and $B = \{b_{ij}\}_{Z\times Z}$ is the emission matrix, where $b_{ij}(\Delta y_k) = \mathcal{N}(\Delta y_k; \mu_{ij}, \sigma_{ij}^2)$ and $\mathcal{N}(.)$ is the Gaussian function. For simplicity, we refer to a difference HMM, as a HMM in the rest of the paper. The ADC creates a VA as a two-state HMM ($Z = 2$) with initial parameters $\lambda_0 = (\pi_0, A_0, B_0)$.

Accordingly, a VA's Gaussian model parameters are exploited to initialize its emission matrix B_0, expressed by (6). Since the Gaussian parameters are the mean and variance of Pdiff, they are used to initialize emission matrix with regard to difference HMM.

$$B(\Delta y_k) = \mathcal{N}\left(\Delta y_k; \begin{bmatrix} 0 & \mu \\ -\mu & 0 \end{bmatrix}, \begin{bmatrix} \sigma^2 & \sigma^2 \\ \sigma^2 & \sigma^2 \end{bmatrix}\right) \tag{6}$$

In order to calculate π_0 and A_0, an operation period of a VA (that we are modeling) is captured in the aggregated signal. For this purpose, we categorize Δy_k that correspond with a VA, by using its Gaussian model, through (5). In addition, time indexes of Δy_k are defined in the data frame. As a result, we extract approximate operation cycles of a VA by using the sign of these power values and their time indexes. To be precise, we match the consecutive Δy_k that have inverse signs (a positive matches a negative), to form the operation cycles, as shown in Fig. 2. In this Figure, the black-dotted bars are classified power values and red rectangles are VA's operation cycles. On the basis of the captured operation, we create an ON/OFF state sequence of a VA. By counting the number of states in this sequence, π_0 and A_0 are computed. In fact, we employ a state-indicator function, based on (7) and (8) to do this. These equations are explained in the model revision phase since they are a rule of the model learner. As a result, a new VA is constructed and stored in the database. The above procedure is done for all new PoI, successively.

As mentioned, the PoI also include the recurrent patterns, which their corresponding VAs have been previously modeled and stored in the database. Therefore, we have a set of VAs (new and previously modeled) that are revised within the model revision phase. As highlighted before, we explain this process for a single VA. ADC revises a VA

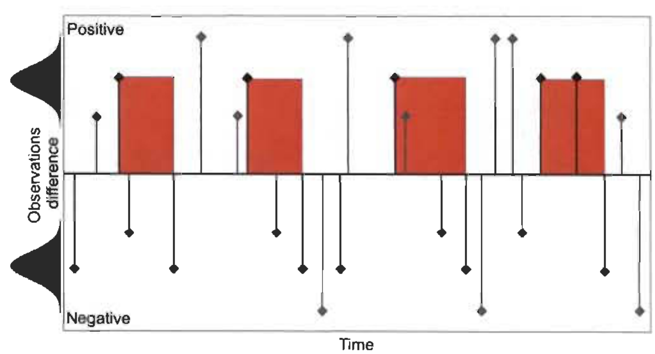

Fig. 2. The schematic of approximate operation cycles of a VA.

through an on-line learning procedure, capable of updating the model parameters by estimating their posterior probabilities. This procedure takes advantage of Viterbi Training (VT) algorithm in order to expedite the training. VT is a logical fit for our method, since it is an unsupervised learning algorithm based on unlabeled data [51]. VT is simpler, more robust, and significantly faster than Baum-Welch algorithm. Therefore, it performs well with regard to an online unsupervised update to HMM parameters [52]. VT algorithm first makes a best-guess to initialize the model parameters. Due to the lack of prior knowledge, we have extracted the initial parameters directly from the aggregated signal. For a previously modeled VA, we use its parameters from the past window. Afterwards, VT (Unlike Baum-Welch algorithm) employs the most likely state sequence to re-estimate HMM parameters. Accordingly, we utilize standard Viterbi algorithm to decode the state sequence of a VA (using its HMM parameters) and capture its best state sequence. In fact, we disaggregate a VA from the aggregated signal in order to estimate its HMM inference. As a result, the most likely state inference is exploited by VT to update a VA's HMM. The state distribution vector and transition matrix are re-estimated by using (7) and (8)

$$\pi_i = \frac{\sum_{n=1}^{N} \mathbf{1}_i(q_n)}{N} \quad 1 \leqslant i \leqslant 2 \tag{7}$$

$$a_{ij} = \frac{\sum_{n=2}^{N} \mathbf{1}_i(q_{n-1})\mathbf{1}_j(q_n)}{\sum_{n=2}^{N} \mathbf{1}_i(q_{n-1})} \quad 1 \leqslant i, j \leqslant 2 \tag{8}$$

where $\mathbf{1}_i(q_n)$ is the state-indicator function, which is one for $q_n = i$ and zero otherwise. q_n is a VA's best state inference at observation n. Actually, the numerator and denominator in (8) are the number of transitions from state i to state j, and the number of transitions from state i, respectively. As mentioned, the Eqs. (7) and (8) are also used to calculate π_0 and A_0. Moreover, the best state sequence, q is used to detect Pdiff that are consistent with its state changes, through (9).

$$\Delta y_n = \Delta y_n \mathbf{1}_i(q_{n-1})\mathbf{1}_j(q_n) \quad 1 \leqslant i \neq j \leqslant 2,\ n \in \{1...N\} \tag{9}$$

Consequently, the mean and variance of these power values are calculated to update a VA's Gaussian model and construct its revised emission matrix based on (6). The model revision phase re-estimates the HMM parameters of all VAs in the database, which have been detected. It can be deduced that ADC adaptively revises VAs' parameters (both their labels and HMMs) by employing their information from the previous time. In fact, our model revision phase can be executed within either the current time window or the occurrence time window. The latter is a time window that starts from the first time (labeled in the database) that a VA has been detected. Regarding the data frame structure, occurrence time window can have a maximum length of one day. The model revision in such a window is mainly preferred, because it can yield more accurate estimation of parameters. Therefore, it can assit with detection of VAs' missing operation sequences from previous times. Indeed, our modeling process gradually enhances the database structure in an adaptive on-line context.

3.2.3. Database management

ADC continuously monitors the database and aggregated signal in order to implement the above mechanisms at every time window. As a result, VAs are constructed and stored in the database. ADC is set to start the process of database construction from a time window with least number of patterns. In this case, we consider the minimum of two patterns. Consequently, it avoids the modeling during peak hours, where the rate of overlapping and the number of invalid patterns are higher. In fact, ADC manages PoI in the following orders to update the database (see Fig. 3).

1- Previous VAs: First, the detected VAs, which have been previously modeled are selected. Consequently, their models are revised and their power profiles are reconstructed and disassociated from the aggregated signal, separately.
2- New VAs: Second, the new VAs are constructed and stored in the database. Subsequently, they are treated like existing models, described in 1.

We have realized that disaggregating the previous VAs first, prevents the database from invalid new ones. In fact, the aggregated signal changes by disassociating the previous VAs from it. Therefore, some of new PoI are not valid for the changed aggregated signal. As a result, ADC rejects these new patterns and accelerates the modeling process.

Accordingly, by disaggregation of VAs' power profiles from the aggregated signal, a residual remains at the end. In the context of a steady-state analysis, the devices such as fridge with considerable transient can cause the load disaggregation practice to fail in capturing either their or other loads' operations during the same period. Such cases result in a residual that can contain the missing operation cycles of the loads. In fact, this situation can be avoided by using an effective preprocessing, generally a high order filtering. However, the preprocessing can cause the loss of operation events of other appliances. Therefore, we develop a residual process that aims to capture the possible missing operations in the remaining signal. Our residual process only looks for the probable operations of previously stored VAs and not constructing new ones. This process employs the pattern detection step to recognize any recurrent patterns in the residual signal. Consequently, it revises any VAs that it detects its pattern in the remaining signal through the model revision phase. Generally, the missing operations are related to VAs that present devices with high transient events like fridge. These operations have not been successfully disassociated through the main process. Therefore, our residual analysis intends to improve the performance of the modeling process by capturing the missing operations of VAs.

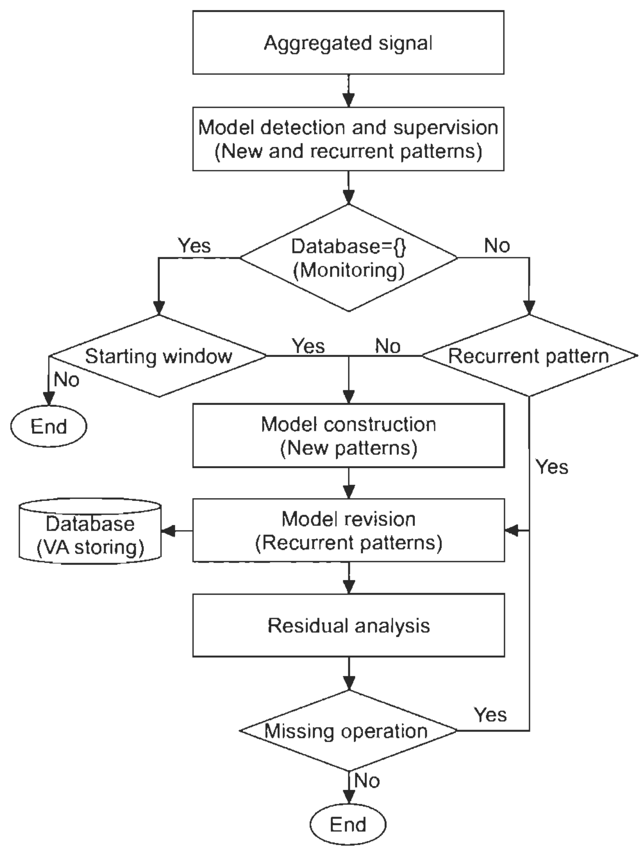

Fig. 3. General structure of the database construction process at every time window (End means that the process moves to the next window).

3.3. Load profiling

Since we have no prior knowledge about existing appliances, we estimate their power profiles. In fact, our ADC is capable of an unsupervised load profiling of VAs. Load profiling can be executed in either current time window or occurrence time window. A VA's load profiling is performed by using Pdiff that correspond with the state changes in its HMM inference based on (9). ADC applies KDE, expressed by (1), to the corresponding Pdiff in order to determine the power value with the highest density. This value is considered as the power consumption of the related VA. Subsequently, the VA's power consumption is multiplied by its state sequence inference in order to build its power profile.

4. Evaluation framework

Our intention, stated in the Section 1 is evaluated based on the following framework.

4.1. Dataset

We employ a publicly available dataset and an experimental data, described as below:

1- ECO (Electricity Consumption and Occupancy) dataset: We utilize the comprehensive ECO dataset, suitable for load disaggregation studies [53]. In fact, in [1], we have demonstrated ECO as a proficient dataset with properties that lack in other databases. In addition, we are interested in load modeling of Electric Water Heater (EWH), due to its influence over total electricity consumption of Quebec houses, where this study is conducted [54,55]. Therefore, we utilize our dataset development tool, discussed in [56] to generate the EWH's profile. Subsequently, we construct our total signal by adding EWH data to ECO aggregated signal. We do not consider a set of targeted appliances due to the lack of prior information. However, our results demonstrate that the constructed VAs in the database include household loads with major power consumption. Therefore, they are comparable with targeted appliances, that are modeled in other studies, which benefit from any kind of prior knowledge.

2- Experimental data: We have developed a data acquisition system to provide our experimental data [57]. Because of stochastic unsupervised nature of the process, the experimental test mainly intends to asses the algorithm capability in a low expectation scenario. This scenario processes the real aggregated data of a set of two household appliances with high energy consumption, consisting of a fridge and an EWH. Although two appliances are targeted, the number of PoI, generated by their aggregated signal account for several VAs (discussed in detail below). This makes our real case worthy of examination.

4.2. Simulation report

Our adaptive database construction approach requires its specific context for results' presentation in order to highlight important matters (which have not been necessitated in other studies).

1- Resulting models: The electrical features of constructed VAs are presented as the final results of the modeling process. VAs can be labeled by using of these features and general information of household appliances.

2- ADC steps: ADC consists of different procedures, which require their own analysis. Accordingly, model detection and construction as the main steps of ADC are analyzed. Furthermore, we illustrate examples of pattern recognition and load profiling processes.

3- Simulation process: Due to the adaptive nature of the algorithm, not only the results, but also the process evolution is elucidated in order to provide an actual evaluation. Furthermore, the structure of the designed database is represented in order to detail its management by ADC within the process. Additionally, the capability of our adaptable procedure to capture the dynamic of the consumption and improve the estimated parameters of VAs is discussed.

4.3. Accuracy metrics

We describe our database construction results by using energy estimation accuracy (10) and F_1-score (11), detailed in [58,59], respectively.

$$Acc = 1 - \frac{\sum_{k=1}^{K} |\widehat{x}_k - x_k|}{2\sum_{k=1}^{K} x_k} \tag{10}$$

where $\widehat{x}_k$ and x_k are power consumption of reconstructed VA and its actual corresponding appliance.

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \tag{11}$$

that $precision = \frac{t_p}{t_p + f_p}$ and $recall = \frac{t_p}{t_p + f_n}$, in which t_p presents true positives (number of correct detection of an appliance's ON state), f_p stands for false positives (number of false detection of an appliance's OFF state as ON), and f_n expresses false negatives (number of false detection of an appliance's ON state as OFF).

The adaptive scheme can maintain the recurrence of a pattern when it is weakened by the other patterns' presence. Nevertheless, regarding our diagnosis purposes, its capability to correctly diagnose the operation state of a VA is evaluated. Accordingly, we interpret increase/decrease in the density of a VA's recurrent pattern as its ON/OFF operation states, respectively. Afterwards, we apply the diagnostic odds ratio (DOR) to our interpretation. DOR is a single indicator of a diagnostic test performance [60]. It is used in medical testing with binary classification as the ratio of the odds of the positivity in disease to the odds of the positivity in non-diseased, described by (12)

$$DOR = \frac{t_p}{f_p} / \frac{f_n}{t_n} \tag{12}$$

that t_n describes true negatives (in our case, number of correct detection of an appliance's OFF state), and other parameters are as above. 95% confidence interval (95%CI) of DOR in terms of $exp[log(DOR) + 1.96 \times SE(log(DOR))]$ is also computed, for which SE is the standard error, defined by (13)

$$SE(log(DOR)) = \sqrt{\frac{1}{t_p} + \frac{1}{t_n} + \frac{1}{f_p} + \frac{1}{f_n}} \tag{13}$$

DOR values range from zero to infinity, which values lower than one represent an erroneous test, a value of one indicates the test inability to discriminate between true and false, and higher values imply better discrimination [60]. Moreover, we examine the pattern recognition results by using diagnostic effectiveness ratio as a simple metric, expressed by (14).

$$Eff = \frac{t_n + t_f}{t_n + t_f + f_p + f_n} \tag{14}$$

Egarter has also used this metric however, diagnostic effectiveness ratio is prevalence-dependent and should always be examined considering other diagnostic accuracy metrics. It is noted that DOR is prevalence-independent [60].

5. Results and evaluation

We have utilized the aggregated power consumption signal in order to examine our proposed approach. The results are presented in a period of one day, considering the length of the data frame. Accordingly, the household database construction results for ECO Houses 2 and 6 are presented in Tables 1 and 2, respectively. These houses consist of appliances with different electrical characteristics. Particularly in [5], the author has demonstrated ECO House 2 as one of the challenging cases for load modeling among three popular datasets. For a clear comprehension of constructed VAs, we have labeled them with regard to actual appliances that they have uncovered.

In both cases, ADC has created VAs that correspond to household appliances' with major power consumption, by use of no prior knowledge. In fact, these appliances, which consume a massive energy in residential houses, are commonly targeted due to energy saving issues. For example, EWH accounts for 20% of electricity bills in Quebec, Canada [61]. We have presented the electrical features of VAs (their mean and variance) since they are sensible. The database of House 2 has comprised 12 VAs among which, 6 have explained actual appliances. On the other side, in the database of House 6, there have been 9 VAs, that 5 of them have corresponded to real loads. Impractical VAs (remaining ones in both cases) have been mostly related to transient and overlapping events, specifically during peak hours. Unlike Kim, we have not assumed a constant variance however, in order to avoid overfitting problems, we have considered an arbitrary upper bound of 700 W [62]. In fact, the algorithm can be improved by analyzing variance stability to prevent leaving it as a free variable [10]. Nonetheless, except for two VAs, our adaptive on-line process has maintained the variance variations. Furthermore, it has successfully managed the variance of all VAs in House 6. Actually, this variable highly varies due to our entirely stochastic unsupervised process. However, we only present the values in the last window of a VA's presence based on its recurrent pattern.

In addition, we have evaluated the main steps of ADC to create VAs. The model construction accuracy has been computed by using reconstructed power profile and state sequence inference of a VA based on (10) and (11), respectively. In order to effectively show the model construction ability, these metrics are only computed for the occurrence time window of a VA. This avoids the imbalance classes, which can affect F_1-score results. Furthermore, it is more practical considering our study that investigates a NILM system with diagnosis purposes. Accordingly, it can be observed that the model construction has achieved high scores in a fully unsupervised process, especially F_1-score. Additionally, without any prior information, it has favorably determined VAs' power values and estimated their energy consumption, considering Acc. However, the model construction accuracy of VA_{11} in House 2 and VA_5 in House 6 has scored low. VA_{11} has a similar power value to VA_8 with a large variance, and its order in the database is after VA_8. Therefore, it has been frequently categorized as VA_8. Actually, VAs are handled in every time window based on their storing order in the database. Moreover, VA_5 presents one of the operation states of coffee maker that has a high-varying power consumption (between 250 W and 400 W) with a very short duration (one second). Consequently, the model construction precision of VA_5 has not scored high specifically, its Acc. Moreover, it can be observed that VA_8 and VA_{10} in House 2 as well as VA_5 and VA_8 in House 6 characterize two different operation states of stove and coffee maker, respectively. This signifies the fact that a thorough unsupervised appliance-level load modeling by using only one source of information is limited, regarding multi-state appliances.

Moreover, the model detection metrics have been calculated for the total windows of analysis (One day). It can be noticed that model detection phase has carried out very accurate results, specifically in recognition of VAs related to regular loads such as stove. The lower results for VAs, presenting periodic loads such as Fridge are mainly due to the loss of their patterns during peak hours. However, DOR results demonstrate the pattern recognition capability to discriminate between operation states of VAs. Additionally, we have considered the results of the residual process for the accuracy reports in the above Tables. The primary goal of residual process is to capture the signatures with high transients since we have avoided a high-order filtering. Our residual phase has captured missing operations of VA_2 in House 2 at 7, 8, and 11AM as well as 6 and 9PM and increased its final accuracy from 93% to 95%. In addition, it has detected VA_1's missing operations in House 6 at 6 and 7AM. However, our adaptive process has been able to detect these operations in the next windows and thus, they are automatically computed in the accuracy.

By comparing VAs of the above experiments for example EWH, it can be deduced that their order is based on their first-time detection. Consequently, they have gradually constructed the database. This demonstrates ADC capability of capturing the dynamic of consumption through continuously monitoring the aggregated signal and uncovering VAs. In addition, through its adaptable procedure, ADC has prevented the database from accumulating false VAs and converged to a specific number of models in both cases. This has been illustrated in Fig. 4 for House 2. Moreover, we have presented the database structure of House 6 for two VAs during one day in Fig. 5. This details the way that we store and manage VAs in the database. In order to make our approach feasible, we have designed an organized database with sufficient information to manage it efficiently. It can be seen that our ADC identifies a VA by five features. 'Name' is the index of a VA that defines its order in the database. 'Pattern' presents its power consumption pattern. 'Trend' describes the density of its pattern and 'Model' is an object that comprises its HMM parameters. These information are updated in every time window. Finally, 'Flag' that contains several cases, which define the appropriate process for a VA. Accordingly, 'S' (Start) presents the first time that a VA has been detected and handled by model construction step. 'IN' means that adaptive process has maintained a VA in

Table 1
Appliance database construction results for ECO House 2.

VA	Model (μ, σ^2)	Model construction accuracy		Model detection accuracy			Actual appliances
		F_1-score	Acc	Eff	DOR (95% CI)	SE	
VA_1	(2750.76, 137.53)	98.5%	94%	89%	2.85 (0.05–158.63)	2.05	EWH
VA_2	(79.8, 3.99)	95%	87.5%	73%	85.8 (3.61–2041)	1.62	Fridge
VA_7	(1854.19, 700)	99.6%	99.7%	95%	141 (2–9917.9)	2.17	Kettle
VA_8	(2352.7, 700)	98.6%	84.6%	92%	45 (1.23–1650.6)	1.84	Stove
VA_{10}	(1192.3, 191.2)	99.3%	98.4%	96%	225 (3.6–14018.5)	2.1	
VA_{11}	(2300.36, 115.02)	77%	66%	96%	225 (3.6–14018.5)	2.1	Dish washer

Table 2
Appliance database construction results for ECO House 6.

VA	Model (μ, σ^2)	Model construction accuracy		Model detection accuracy			Actual appliances
		F_1-score	Acc	Eff	DOR (95% CI)	SE	
VA_1	(64.83, 28.73)	98.48%	92.7%	89%	25.8 (0.81–819.5)	1.76	Fridge
VA_2	(2817.26, 101.41)	99.68%	98.8%	81%	41.88 (1.95–897.66)	1.56	EWH
VA_5	(257.08, 12.85)	88.35%	50.26%	92%	45 (1.23–1650.6)	1.84	Coffee maker
VA_8	(1286.04, 322.99)	97.8%	75.9%	95%	141 (2–9917.9)	2.17	
VA_9	(2088.64, 208.86)	98.26%	62.43%	92%	45 (1.23–1650.6)	1.84	Kettle

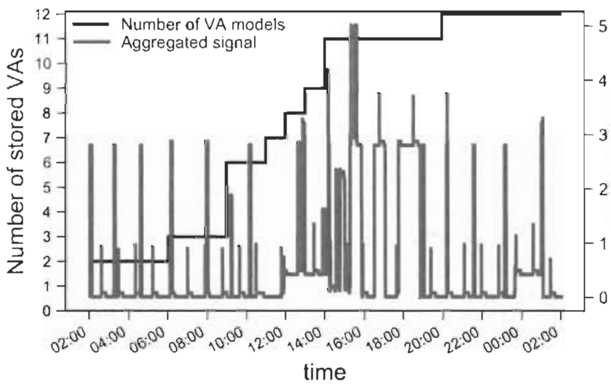

Fig. 4. ADC results of capturing the dynamic of aggregated power consumption of ECO House 2 through recognizing its recurrent patterns and creating their corresponding VAs.

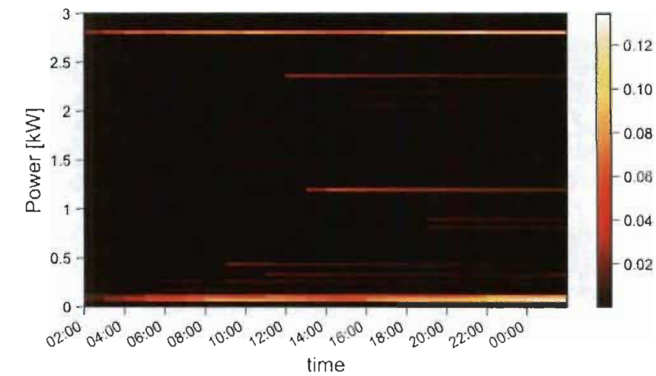

Fig. 6. ADC results of recurrent pattern recognition of aggregated signal of ECO House 2.

the modeling procedure due to the recurrence of its pattern. Therefore, it has been managed by model revision step. 'OUT' shows the time that a VA has been excluded from the process. In 'Flag', 'time' represents the day and the hour. The great advantage of 'Flag', enabled by our adaptive on-line approach, is that ADC can efficiently manage a VA and in turn, accelerate its modeling process.

Moreover, we have depicted the results of recurrent pattern recognition for House 2 in Fig. 6. The color fluctuation from dark to light presents low and high density regions, respectively. This Figure demonstrates the procedure capability to recognize new patterns and maintain recurrent patterns. Although the actual appliances are unknown, it is possible to propose hypotheses. The recurrent patterns, related to periodic loads are observable at all times. For example, at the bottom of the Figure, the continuous increase in density value with low power consumption can be attributed to appliances such as fridge. However, a slight reduction in density of this pattern during peak hours (12–16 h) can be related to its overlapping with other patterns. Nevertheless, the results demonstrates that our adaptive scheme is able to maintain the presence of a pattern and avoids the loss of its recurrent pattern. On the other hand, recurrent patterns of regular appliances such as stove diminish steadily. Additionally, there are also other patterns, related to transient events, load combinations, and overlapping that can challenge the pattern recognition of actual loads. In fact, our analysis demonstrates that a memory-less pattern recognition can periodically miss the recurrence of patterns and their operation times. This can lead to define mistakenly new VAs, lose their probable operations, and renew their starting time, which is important for adaptive on-line training.

In addition, we have illustrated unsupervised load profiling for

Name: VA_2														
Pattern: 2798.38														
Trend: 0.0764														
Model														
π	[0.8675 0.1324]													
A	[[9.9974e-01 2.5349e-04] [1.6599e-03 9.9834e-01]]													
B	[[0. 2817.26] [-2817.26 0.]]	[[101.41. 101.41] [101.41 101.41]]												
Flag														
Time	(2,2)	(2,3)	(2,4)	(2,5)	(2,6)	(2,7)	(2,8)	(2,9)	(2,10)	(2,11)	(2,12)	(2,13)		
Case	S	IN	IN	IN	IN	IN	IN	IN	IN	IN	IN	IN		
Time	(2,14)	(2,15)	(2,16)	(2,17)	(2,18)	(2,19)	(2,20)	(2,21)	(2,22)	(2,23)	(3,0)	(3,1)		
Case	IN	IN	IN	IN	IN	IN	IN	IN	IN	IN	IN	IN		

Name: VA_9												
Pattern: 2026.86												
Trend: 0.0022												
Model												
π	[0.9936 0.0064]											
A	[[9.9986e-01 1.3980e-04] [2.1739e-02 9.7826e-01]]											
B	[[0. 2088.64] [-2088.64 0.]]	[[208.86 208.86] [208.86 208.86]]										
Flag												
Time	(2,2)	(2,3)	(2,4)	(2,5)	(2,6)	(2,7)	(2,8)	(2,9)	(2,10)	(2,11)	(2,12)	(2,13)
Case	OUT	OUT	OUT	OUT	OUT	OUT	S	IN	OUT	OUT	OUT	OUT
Time	(2,14)	(2,15)	(2,16)	(2,17)	(2,18)	(2,19)	(2,20)	(2,21)	(2,22)	(2 23)	(3,0)	(3,1)
Case	OUT	OUT	OUT	OUT	OUT	OUT	OUT	OUT	OUT	OUT	OUT	OUT

Fig. 5. The schematic of the database structure of ECO House 6.

House 2 in Fig. 7. Load profiling has been presented for occurrence time window of VAs. ADC ability to manage the recurrent patterns within the modeling process has been also shown in this Figure. It can be seen that VA_7 (see Table 1) has not been profiled at the end of the process since it has been excluded by ADC ('OUT' case). This is the case for VA_9 in House 6, as shown in Fig. 5. As it can be concluded from Table 1, VA_{11} is not efficient to build an accurate power profile. It should be highlighted that VA_{11} performs relatively efficient during the procedure, which is important for on-line applications. However, we have presented limited examples to avoid an exhaustive discussion. Indeed, Fig. 7 has been presented to indicate the effectiveness of created VAs to reconstruct the power profiles of actual loads.

Moreover, the ability of our adaptive learning as a retrievable procedure to improve the model parameters has been explored. We have described this ability based on better recognition of operation cycles of a VA due to its upgrade within time. This has been illustrated in Figs. 8 and 9 for VA_1 in Houses 2 and 6, respectively. The actual appliances' signature has been used to show the results' efficiency. It can be observed that the adaptable procedure is able to modify a failure (red rectangle) to a success (blue rectangle) by revising VAs' parameters. However, the required time to correct a faulty recognition is different. Moreover, it can be realized that the ability of adaptive process to improve the model parameters can benefit more VAs with frequent operation (VA_1 and VA_2 in both cases). Indeed, a failure can be attributed to model deficiency for different reasons. Nevertheless, our adaptable structure, designed with an on-line learning phase is capable of recovery from the failure.

Although the public datasets are actually real-world measured data, we have also utilized the data of our developed acquisition system. As a thoroughly stochastic process, the intention is to explore the approach performance in a low expectation scenario. Accordingly, the process has been targeted to construct the VAs, corresponding to power measurements of a fridge and an EWH. The results of database construction have been presented in Table 3. It can be seen that ADC has successfully constructed VAs, related to our targeted loads. However, the model detection accuracy of VA_1 is very low that demonstrates its inadequacy of discrimination between operation states. Notwithstanding our EWH's one state operation, there are two VAs that describe it. To be precise, as it can be observed in Fig. 10, our low expectation scenario (two appliances) is a challenging one. From recurrent patterns with high densities, it can be thought that several loads exist in the aggregated signal. Fridge has high lengthy transients with steady-state power variations. Therefore, there are 9 recurrent patterns that only belong to Fridge. As a result, the process has frequently lost its main pattern. Furthermore, EWH exposes 5 recurrent patterns. In fact, at 12PM, a variation in EWH's power consumption has generated different patterns that resulted in a new VA (VA_3). Nonetheless, not only our ADC has maintained the main patterns of VAs but also it has constructed a database of only three VAs and rejected all invalid ones. Indeed, our experimental test can be a case for diagnosis of either acquisition system or appliances, particularly regarding the behavior of our fridge. The above notes has made it worth to investigate a low expectation scenario of real-world data.

6. Discussion

In fact, our thorough study necessitates a discussion, which is provided in the followings.

6.1. Our approach

In this study, we have investigated the essential prerequisite of a NILM system for diagnosis purposes. Accordingly, we have designed a time-variant load modeling system (regarding the dynamic of power consumption) with two important abilities, the recognition of new appliances and the continuous learning of their parameters. Indeed, these abilities are important for diagnosis systems that require knowledge about new loads and their standard behavior. Consequently, we have proposed our approach in terms of household appliances database construction. We have utilized three important methods to formulate our database constructor with regard to its features, as follow:

1- Our load modeling structure only uses the measured data of the aggregated signal. Therefore, it is advised to employ a method, capable of operating with less or no initial information [2]. Therefore, notwithstanding its complexity, we have utilized an unsupervised approach.
2- In addition, our time-varying analysis with less/no prior knowledge signifies the exploitation of an adaptive structure to extract the preserved sequential information in the data [46]. As a result, by using the adaptive estimation of appliances' model parameters, we have developed a thoroughly adaptable procedure for an effective interpretation of their behavior.
3- Furthermore, an efficient ALM scheme mostly targets the devices with high power consumption, whose their accurate energy estimation can assist in a notable cost reduction. Accordingly, we have used the state-of-the-art method of HMM that is able to build robust models of household major loads.

6.2. Comparative study

This study is not presenting a new load disaggregation algorithm to be compared with existing load disaggregators. In fact, the database construction approach has not been adequately explored, especially in this scale. Moreover, there are not specific studies with the same objective to provide a fair comparison. Accordingly, we have provided detailed results with a thorough discussion to enable a convenient evaluation. Nevertheless, we have developed a fully unsupervised method without any prior knowledge. From this standpoint, Hart, Kim, and Guo have provided a similar analysis. However, Hart and Kim have utilized their own experimental data to report the results, that prevents a sensible comparison. In addition, Kim has not provided appliance-level results and except for fridge, his targeted appliances have not been among household devices with major loads. Guo has used a public dataset however, he has neglected to report disaggregation results for comparison. To the best of our knowledge, unsupervised disaggregation studies have mostly considered a set of initializations by use of general information. However, due to diversity of household appliances in types and brands (for example fridge in our case studies), providing an appropriate space of information is difficult. Therefore, they have considered more specific information that has resulted in a likely semi-supervised analysis (an unsupervised method with specific priors). Indeed, general information can be beneficial since an analysis with no prior knowledge can decline an accurate interpretation of the results

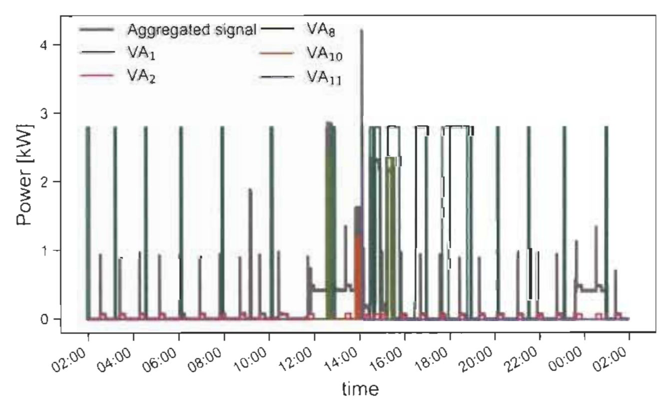

Fig. 7. Unsupervised load profiling of constructed VAs' in the database of ECO House 2 during one day.

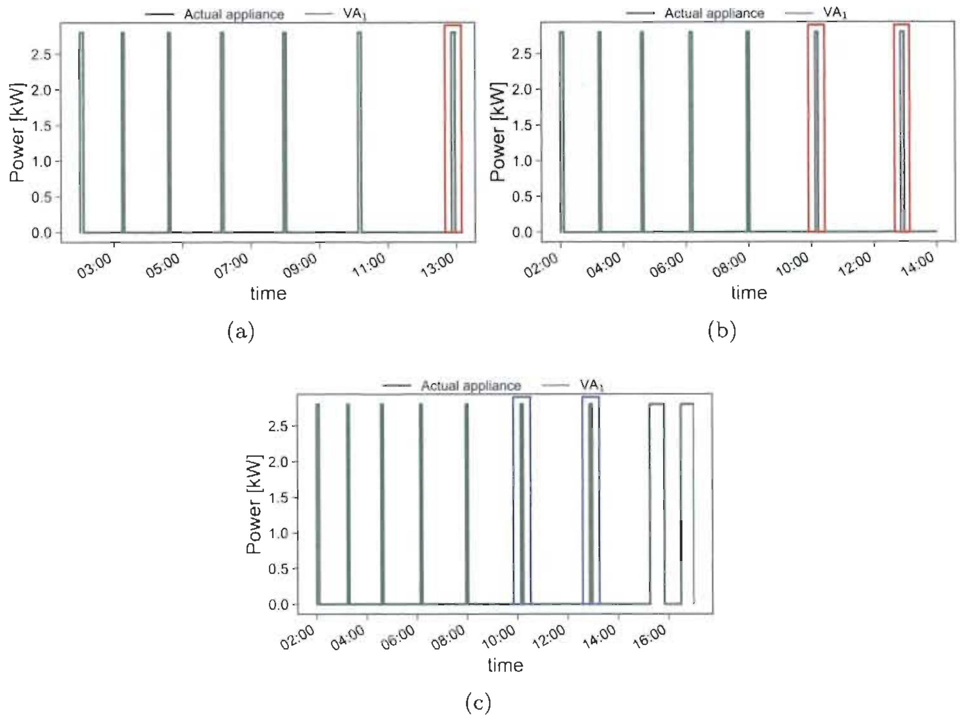

Fig. 8. The adaptive process capability of recognizing the correct operation cycles of VA$_1$ in ECO House 2 by revising its model parameters through the time.

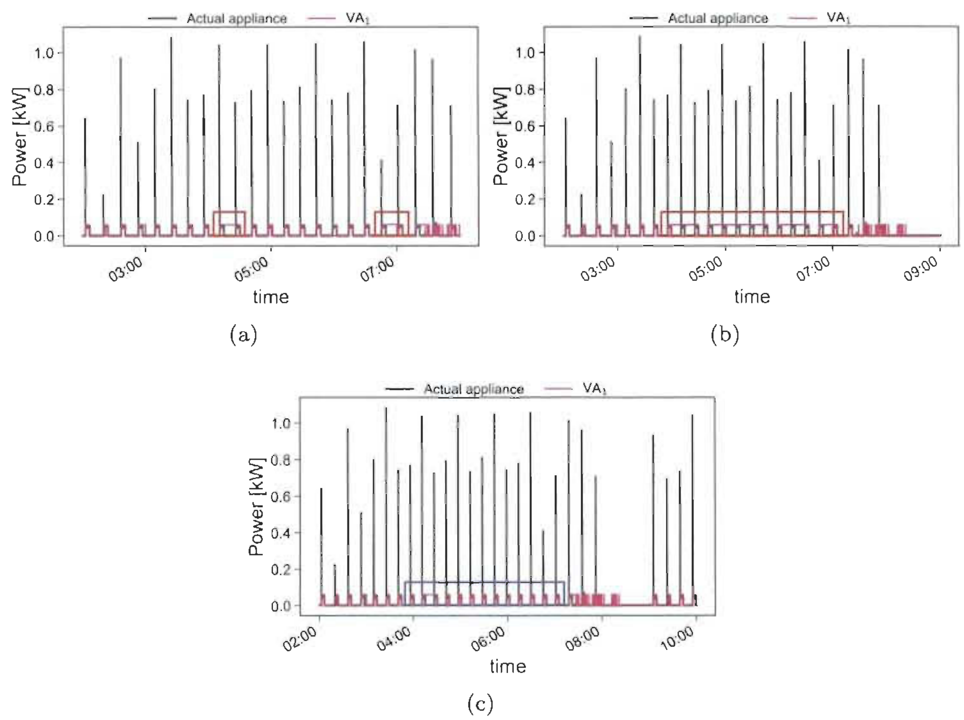

Fig. 9. The adaptive process capability of recognizing the correct operation cycles of VA$_1$ in ECO House 6 by revising its model parameters through the time.

and decrease the performance of the modeling process. However, we propose to employ these information in the level of housing stock to enhance its application by reducing uncertainties.

Moreover, it should be noted that the recent studies tend to report the disaggregation results in the scale of entire house. The critical downside of this aspect is that it does not satisfy customers' preferences and producers' interests, who seek the energy reports of individual appliances. Furthermore, such assessment is not suited for our approach, which outlines appliance-level model construction. Notwithstanding the above note, the performance of the ADC is evaluated in terms of a disaggregator (regarding load disaggregation studies) in order to deeply discuss this aspect of our proposed method, as below.

1- Feature choice: We have analyzed steady-state operation of household appliances, which can be executed through a system with low-sampling frequency. In fact, regular smart meters are able to provide data in 1 Hz sampling frequency to be used for load disaggregation algorithms [18].
2- Accuracy: A disaggregator is required to have a minimal accuracy of

Table 3
Appliance database construction results using experimental data.

VA	Model (μ, σ^2)	Model construction accuracy		Model detection accuracy			Actual appliances
		F_1-score	Acc	Eff	DOR	SE	
					(95% CI)		
VA_1	(45.59, 29.98)	95%	86%	21%	0.23 (0.004–12.6)	2.06	Fridge
VA_2	(2758.99, 700)	99.8%	98.6%	73%	27.5 (1.3–560)	1.5	EWH
VA_3	(2682.75, 473.16)			96%	301 (5.09–17794.6)	2.08	

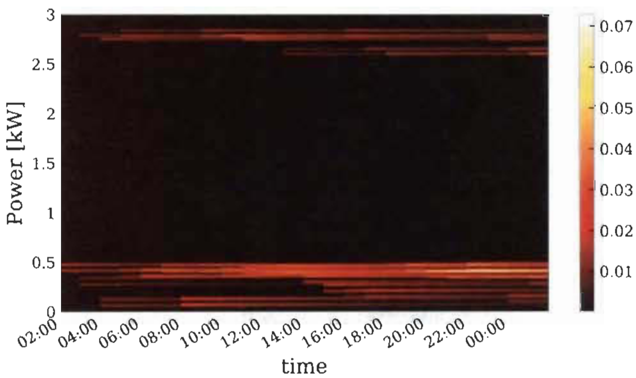

Fig. 10. ADC results of recurrent pattern recognition of aggregated signal of experimental test.

80% [9]. However, our extensive method is not only a disaggregator because, it consists of two main processes of 'model detection and supervision' as well as 'model construction and revision'. In accordance with each process, a set of accuracy metrics have been presented. Accordingly, ADC has met acceptable results for all cases, and high accuracy scores for the majority of them (considering all accuracy metrics). It must be highlighted that the modeling process is influenced by the recurrent pattern recognition step, which makes the numerical analysis of our method's accuracy, particular. In order to demonstrate this fact, we have utilized our constructed model of VA_9 in House 6 for merely a load disaggregation, that has resulted in F1-score of 99.4% and Acc of 98%. In addition, the studies that mention the above accuracy have conducted either supervised or semi-supervised methods. Therefore, they have had access to submeter measurements or a set of priors. To be precise, they have a set of known appliances. Indeed, it is challenging to infer the power consumption's model of an unknown load in a modeling procedure with no prior knowledge (modeling from scratch). This is the reason that our energy estimation accuracy has lower scores.

3- No algorithm training: This aspect refers to a disaggregator that does not require any human intervention. Our ADC employs an unsupervised method with no prior knowledge and thus, notably reduces human involvement in the set-up phase. Due to supervised and semi-supervised nature of the most load disaggregation methods, human efforts is required in initial model construction. In addition, the paper tackles the concept of appliances' automatic labeling by using an unsupervised load profiling in order to reduce final human intervention. This concept has been mainly ignored in previous studies. In fact, the necessity for human supervision is a fundamental issue of NILM systems. This issue can hinder real online applications, reduce customer motivations after purchase, and influence the usability of manufactured products. By constructing a household database of virtual appliances, this paper intends the maximum reduction of human intervention.

4- (Near) real-time application: An on-line learning system with dynamic HMM parameters has been proposed in this paper. It employs a set of low-complex algorithms to expedite the whole process of appliance database construction. In fact, load disaggregators have mostly encountered an off-line phase and the concept of on-line have been proposed for an on-line disaggregation.

5- Type of appliances: ADC constructs the models of finite-state load appliances in terms of two-state loads. Therefore, it cannot identify multi-state appliances and thus, it considers them as a composition of two-state loads. In fact, due to unsupervised nature of our method that use no prior knowledge about household appliances, it is almost impossible to identify multi-state appliances. These appliances have a wide-range of power consumption based on their brand, for example washing machines. Therefore, their recognition requires general information or sub-metered data compared to periodic loads with similar power consumption such as fridge. Nevertheless, it should be noted that a great advantage of our ADC is to recognize the type of a pattern (regular or periodic) by continuous monitoring of its value and operating time. Therefore, it can provide hypotheses about the type of a load, for example multi-state devices that are normally regular loads (their operation period is limited). In addition, our proposed method has difficulty with modeling of identical loads. Therefore, in the House 2, we have extracted Freezer's load profile from the aggregated signal. Indeed, the analysis of periodic loads with highly similar power consumption values (such as fridge and freezer in ECO House 2) is a fundamental issue of NILM studies, which has been mainly ignored. One reason can be attributed to the fact that, this is a rear scenario among popular datasets that have been utilized for load disaggregation, such as REDD (Reference Energy Disaggregation Data Set) [58]. In fact, our set of appliances is comparable with other studies. It should be added that continuously variable loads have not been in the scope of this analysis. Actually, most of disaggregators have ignored these loads since, normally they are not among household appliances with major power consumption.

7. Conclusions

In this paper, the approach of adaptive on-line unsupervised appliance-level load modeling has been proposed. We have designed a time-variant load modeling procedure for load diagnosis goals of NILM. In fact, the disaggreation methods have been the focal point of NILM studies, that has caused its diagnosis goal to be ignored. Therefore, we have provided a thorough analysis of essential prerequisite of a NILM system with diagnosis purposes. Our proposed approach has resulted in an autonomous household database construction system. Our future studies focus on the improvement of our household database constructor and its utilization for diagnosis systems.

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References

[1] Hosseini SS, Agbossou K, Kelouwani S, Cardenas A. Non-intrusive load monitoring through home energy management systems: A comprehensive review. Renew Sustain Energy Rev 2017;79(April 2016):1266–74. https://doi.org/10.1016/j.rser.2017.05.096.

[2] Shaw SR, Leeb SB, Norford LK, Cox RW. Nonintrusive load monitoring and diagnostics in power systems. IEEE Trans Instrum Meas 2018;57(7). https://doi.org/10.1109/TIM.2008.917179.

[3] Hart G. Nonintrusive appliance load monitoring. Proc IEEE 1992;80(12):1870–91. https://doi.org/10.1109/5.192069.

[4] Alahakoon D, Yu X. Smart electricity meter data intelligence for future energy systems: a survey. IEEE Trans Industr Inf 2016;12(1):425–36. https://doi.org/10.1109/TII.2015.2414355.

[5] Pöchacker M, Egarter D, Elmenreich W. Proficiency of power values for load disaggregation. IEEE Trans Instrum Meas 2016;65(1):46–55. https://doi.org/10.1109/TIM.2015.2477156.

[6] Kong W, Dong ZY, Ma J, Hill D, Zhao J, Luo F. An extensible approach for non-intrusive load disaggregation with smart. Meter Data, IEEE Trans Smart Grid 2016;3053(c):1. https://doi.org/10.1109/TSG.2016.2631238.

[7] Parson O, Ghosh S, Weal M, Rogers A. An unsupervised training method for non-intrusive appliance load monitoring. Artif Intell 2014;217:1–19. https://doi.org/10.1016/j.artint.2014.07.010.

[8] Kelly J, Knottenbelt W. Neural NILM. Proceedings of the 2nd ACM international conference on embedded systems for energy-efficient built environments - BuildSys '15 New York, New York, USA: ACM Press; 2015. p. 55–64. https://doi.org/10.1145/2821650.2821672.

[9] Makonin S, Popowich F, Bajic IV, Gill B, Bartram L. Exploiting HMM sparsity to perform online real-time nonintrusive load monitoring. IEEE Trans Smart Grid 2016;7(6):2575–85. https://doi.org/10.1109/TSG.2015.2494592.

[10] Henao N, Agbossou K, Kelouwani S, Dube Y, Fournier M. Approach in nonintrusive Type I load monitoring using subtractive clustering. IEEE Trans Smart Grid 2015;8(2):812–21. https://doi.org/10.1109/TSG.2015.2462719.

[11] Henao N, Agbossou K, Kelouwani S, Hosseini S, Fournier M. Power estimation of multiple two-state loads using a probabilistic non-intrusive approach. Energies 2018;11(1):88. https://doi.org/10.3390/en11010088.

[12] Zhao B, Stankovic L, Stankovic V. On a training-less solution for non-intrusive appliance load monitoring using graph signal processing. IEEE Access 2016;4:1784–99. https://doi.org/10.1109/ACCESS.2016.2557460.

[13] Abubakar I, Khalid S, Mustafa M, Shareef H, Mustapha M. Application of load monitoring in appliances energy management – A review. Renew Sustain Energy Rev 2017;67:235–45. https://doi.org/10.1016/j.rser.2016.09.064.

[14] Tang G, Wu K, Lei J. A distributed and scalable approach to semi-intrusive load monitoring. IEEE Trans Parallel Distrib Syst 2016;27(6):1553–65. https://doi.org/10.1109/TPDS.2015.2470238.

[15] Lin Y-H, Tsai M-S. Development of an improved time-frequency analysis-based nonintrusive load monitor for load demand identification. IEEE Trans Instrum Meas 2014;63(6):1470–83. https://doi.org/10.1109/TIM.2013.2289700.

[16] Du L, Restrepo JA, Yang Y, Harley RG, Habetler TG. Nonintrusive, self-organizing, and probabilistic classification and identification of plugged-in electric loads. IEEE Trans Smart Grid 2013;4(3):1371–80. https://doi.org/10.1109/TSG.2013.2263231.

[17] Zhu T, Shaw SR, Leeb SB. Electric load transient recognition with a cluster weighted modeling method. IEEE Trans Smart Grid 2013. https://doi.org/10.1109/TSG.2013.2256804.

[18] Carrie Armel K, Gupta A, Shrimali G, Albert A. Is disaggregation the holy grail of energy efficiency? The case of electricity. Energy Policy 2013;52:213–34. https://doi.org/10.1016/j.enpol.2012.08.062.

[19] Egarter D, Bhuvana VP, Elmenreich W. PALDi: Online load disaggregation via particle filtering. IEEE Trans Instrum Meas 2015. https://doi.org/10.1109/TIM.2014.2344373.

[20] Bonfigli R, Felicetti A, Principi E, Fagiani M, Squartini S, Piazza F. Denoising autoencoders for non-intrusive load monitoring: improvements and comparative evaluation. Energy Build 2018;158:1461–74. https://doi.org/10.1016/j.enbuild.2017.11.054.

[21] He K, Stankovic L, Liao J, Stankovic V. Non-intrusive load disaggregation using graph signal processing. IEEE Trans Smart Grid 2018;9(3):1739–47. https://doi.org/10.1109/TSG.2016.2598872.

[22] De Baets L, Ruyssinck J, Develder C, Dhaene T, Deschrijver D. On the Bayesian optimization and robustness of event detection methods in NILM. Energy Build 2017;145:57–66. https://doi.org/10.1016/j.enbuild.2017.03.061.

[23] Asres MW, Girmay AA, Camarda C, Tesfamariam GT. Non-intrusive load composition estimation from aggregate ZIP load models using machine learning. Int J Electr Power Energy Syst 2019;105(January 2018):191–200. https://doi.org/10.1016/j.ijepes.2018.08.016.

[24] De Baets L, Develder C, Dhaene T, Deschrijver D. Detection of unidentified appliances in non-intrusive load monitoring using siamese neural networks. Int J Electr Power Energy Syst 2019;104(July 2018):645–53. https://doi.org/10.1016/j.ijepes.2018.07.026.

[25] Tsai M-S, Lin Y-H. Modern development of an adaptive non-intrusive appliance load monitoring system in electricity energy conservation. Appl Energy 2012;96:55–73. https://doi.org/10.1016/j.apenergy.2011.11.027.

[26] Chang HH, Lian KL, Su YC, Lee WJ. Power-spectrum-based wavelet transform for nonintrusive demand monitoring and load identification. IEEE Trans Ind Appl 2014. https://doi.org/10.1109/TIA.2013.2283318.

[27] Lai Y-X, Lai C-F, Huang Y-M, Chao H-C. Multi-appliance recognition system with hybrid SVM/GMM classifier in ubiquitous smart home. Inf Sci 2013;230:39–55. https://doi.org/10.1016/j.ins.2012.10.002.

[28] Wang AL, Chen BX, Wang CG, Hua D. Non-intrusive load monitoring algorithm based on features of V-I trajectory. Electric Power Syst Res 2018;157:134–44. https://doi.org/10.1016/j.epsr.2017.12.012.

[29] Berges ME, Goldman E, Matthews HS, Soibelman L. Enhancing electricity audits in residential buildings with nonintrusive load monitoring. J Ind Ecol 2010;14(5):844–58. https://doi.org/10.1111/j.1530-9290.2010.00280.x.

[30] Iwayemi A, Zhou C. SARAA: semi-supervised learning for automated residential appliance annotation. IEEE Trans Smart Grid 2017;8(2):779–86. https://doi.org/10.1109/TSG.2015.2498642.

[31] Gillis JM, Alshareef SM, Morsi WG. Nonintrusive load monitoring using wavelet design and machine learning. IEEE Trans Smart Grid 2016;7(1):320–8. https://doi.org/10.1109/TSG.2015.2428706.

[32] Gillis JM, Chung JA, Morsi WG. Designing new orthogonal high-order wavelets for nonintrusive load monitoring. IEEE Trans Industr Electron 2018;65(3):2578–89. https://doi.org/10.1109/TIE.2017.2739701.

[33] Basu K, Debusschere V, Bacha S, Maulik U, Bondyopadhyay S. Nonintrusive load monitoring: a temporal multilabel classification approach. IEEE Trans Industr Inf 2015;11(1):262–70. https://doi.org/10.1109/TII.2014.2361288.

[34] De Baets L, Ruyssinck J, Develder C, Dhaene T, Deschrijver D. Appliance classification using VI trajectories and convolutional neural networks. Energy Build 2018;158:32–6. https://doi.org/10.1016/j.enbuild.2017.09.087.

[35] Singh S, Majumdar A. Deep sparse coding for non-intrusive load monitoring. IEEE Trans Smart Grid 2018;9(5):4669–78. https://doi.org/10.1109/TSG.2017.2666220.

[36] Singhal V, Maggu J, Majumdar A. Simultaneous detection of multiple appliances from smart-meter measurements via multi-label consistent deep dictionary learning and deep transform learning. IEEE Trans Smart Grid 2018;3053(c):1. https://doi.org/10.1109/TSG.2018.2815763.

[37] Vann JM, Karnowski T, Anderson AL. Classification of unintended radiated emissions in a multi-device environment. IEEE Trans Smart Grid 2018;PP(c). https://doi.org/10.1109/TSG.2018.2883795. 1–1.

[38] Nascimento PPMd. Applications of deep learning techniques on NILM, Ph.D. thesis. Federal University of Rio de Janeiro; 2016.

[39] Zoha A, Gluhak A, Imran M, Rajasegarar S. Non-intrusive load monitoring approaches for disaggregated energy sensing: a survey. Sensors 2012;12(12):16838–66. https://doi.org/10.3390/s121216838.

[40] Zeifman M, Roth K. Viterbi algorithm with sparse transitions (VAST) for non-intrusive load monitoring. IEEE Symp Compon Intell Appl Smart Grid (CIASG) IEEE; 2011. p. 1–8. https://doi.org/10.1109/CIASG.2011.5953328.

[41] Kolter Z, Jaakkola T. Approximate Inference in Additive Factorial HMMs with Application to Energy Disaggregation. Proc Int Conf Arti Intell Statist 2012;XX:1472–82.

[42] Kim H, Marwah M, Arlitt M, Lyon G, Han J. Unsupervised disaggregation of low frequency power measurements. Proceedings of the 2011 SIAM international conference on data mining Philadelphia, PA: Society for Industrial and Applied Mathematics; 2011. p. 747–58. https://doi.org/10.1137/1.9781611972818.64.

[43] Johnson MJ, Willsky AS. Bayesian nonparametric hidden semi-markov models. J Machine Learn Res 2012;14:673–701.

[44] Guo Z, Wang ZJ, Kashani A. Home appliance load modeling from aggregated smart meter data. IEEE Trans Power Syst 2015;30(1). https://doi.org/10.1109/TPWRS.2014.2327041.

[45] Tabatabaei SM, Dick S, Xu W. Towards non-intrusive load monitoring via multi-label classification. IEEE Trans Smart Grid 2016;3053(c):1. https://doi.org/10.1109/TSG.2016.2584581.

[46] Miao Yun-Qian. Adaptive learning algorithms for non-stationary data, Ph.D. thesis. University of Waterloo; 2015.

[47] Yang Z, Xiang Y, Xie K, Lai Y. Adaptive method for Nonsmooth nonnegative matrix factorization. IEEE Trans Neural Networks Learn Syst 2017;28(4):948–60. https://doi.org/10.1109/TNNLS.2016.2517096.

[48] Vine D, Buys L, Morris P. The effectiveness of energy feedback for conservation and peak demand: a literature review. Open J Energy Efficiency 2013;02(01):7–15. https://doi.org/10.4236/ojee.2013.21002.

[49] Hahn PR, Martin R, Walker SG. On recursive Bayesian predictive distributions. J Am Stat Assoc 2015.

[50] Parson O, Ghosh S, Weal M, Rogers A. Non-intrusive load monitoring using prior models of general appliance types. Proceedings of the 26th AAAI conference on artificial intelligence. 2012. p. 356–62.

[51] Cohen SB, Smith NA. Viterbi training for PCFGs: hardness results and competitiveness of uniform initialization. 48th Annual meeting of association for computational linguistics, July 2010. 2010. p. 1502–11.

[52] Allahverdyan AE, Galstyan A. Comparative analysis of Viterbi training and maximum likelihood estimation for HMMs. http://arxiv.org/abs/1312.4551.

[53] Beckel C, Kleiminger W, Cicchetti R, Staake T, Santini S. The ECO data set and the performance of non-intrusive load monitoring algorithms. Proc. 1st ACM Conf Embedded Syst 2014. p. 80–9. https://doi.org/10.1145/2674061.2674064.

[54] Natural Resources Candada, Energy Fact Book 2016–2017; 2016. URL https://www.nrcan.gc.ca.

[55] Xu Z, Diao R, Lu S, Lian J, Zhang Y. Modeling of electric water heaters for demand response: a baseline PDE model. IEEE Trans Smart Grid 2014;5(5):2203–10.

https://doi.org/10.1109/TSG.2014.2317149.
[56] Hosseini S, Kelouwani S, Agbossou K, Cardenas A, Henao N. A semi-synthetic dataset development tool for household energy consumption analysis. IEEE Int Conf Ind Tech (ICIT) 2017. p. 564–9. https://doi.org/10.1109/ICIT.2017.7915420.
[57] Cardenas A, Agbossou K, Guzman C. Development of real-time admittance analysis system for residential load monitoring. 2016 IEEE 25th international symposium on industrial electronics (ISIE), vol. 2016- Novem. IEEE; 2016. p. 696–701. https://doi.org/10.1109/ISIE.2016.7744974.
[58] Kolter JZ, Johnson MJ. REDD: a public data set for energy disaggregation research. SustKDD workshop 2011(1):1–6.
[59] Makonin S, Popowich F. Nonintrusive load monitoring (NILM) performance evaluation. Energ Effi 2015;8(4):809–14. https://doi.org/10.1007/s12053-014-9306-2.
[60] Glas AS, Lijmer JG, Prins MH, Bonsel GJ, Bossuyt PM. The diagnostic odds ratio: a single indicator of test performance. J Clin Epidemiol 2003;56(11):1129–35. https://doi.org/10.1016/S0895-4356(03)00177-X.
[61] Hot water — Hydro-Québec. http://www.hydroquebec.com/residential/energy-wise/hot-water/.
[62] Henao N, Kelouwani S, Agbossou K, Dube Y. Active power load modeling based on uncertainties for Non Intrusive Load Monitoring. IEEE 25th Int Symp Ind Electron (ISIE) 2016. p. 684–9. https://doi.org/10.1109/ISIE.2016.7744972.

3.4 On-line anomaly detection approach

3.4.1 Background

The concept of household appliances' anomaly detection has been the third important element of an ALM system that has drawn our interest. Behavior that does not comply with the expected manner, which is characterized based on the definition of the normality, can be attributed to anomaly [53]. Particularly, the focal point of our analysis is the operation-time anomaly detection for both technical and mathematical reasons. Technically, household electrical circuits have been designed to capture a load with faulty operation power (like a defective washing machine that has current leakage) rather than one with anomalous operation time (like a functioning stove that is left ON). Furthermore, household devices with notable electricity consumption are mainly finite-state loads such as refrigerators, stoves, and EWH that mostly advertise their anomalous behavior through operation time deviations. Mathematically, the operation time of an electrical appliance is straightforward to model, particularly with regard to state-of-the-art methods. For example, in the context of probabilistic models, the likelihood estimation of a refrigerator's operation sequence compared to its state sequence shows notably higher variations. In fact, due to power consumption transients and fluctuations of a refrigerator, the examination of its operation sequence requires an exact model of power consumption that is not the case for its state sequence. Additionally, the anomaly detection of appliances can be explored in both aggregate and appliance levels. Nevertheless, state-of-the-art NILM (aggregate level) methods are not adequate to provide efficient anomaly detection and thus, diagnosis services [31], [57]. Therefore, an appliance-level anomaly detection analysis has been considered that focuses on operation-time deviations. This idea is signified with future low-priced smart plug technologies. This analysis targets an on-line manner where a connected structure continuously monitors and analyzes each data arrival to capture possible anomalies. Besides, experimentation with actual anomaly scenarios has been another motivation of this analysis that has been neglected in other relevant studies [32], [57].

3.4.2 Methodology

An appliance-level analysis of anomaly promotes the exploitation of techniques that are low-priced, computationally inexpensive, and comprehensible specifically, from the view of customers. Accordingly, the energy and average power consumption information that are also compatible with smart metering technologies have been utilized for the anomaly study. Moreover, the refrigerator has been targeted as the appliance candidate due to the fact that it is a universal household device with intensive consumption, which can be subject to different anomaly conditions. In order to permit real implementation, the entire examination has been done by using the real data of our acquisition system. Our methodology to execute the third study is provided through the following phases that have been illustrated in Figure 3-3. In this Figure, the online anomaly detection procedure is initialized with a threshold that is required to identify ON/OFF operation states of appliances candidate.

- First, normal and anomalous behaviors of the appliances candidate are explored through analyzing their energy and average power consumption factors based on different anomaly scenarios. This analysis focuses on the examination of the Probability Density Function (PDF) of these factors. Accordingly, it demonstrates the effectiveness of the information that is extracted from cyclic operations of the targeted loads to capture an anomaly.

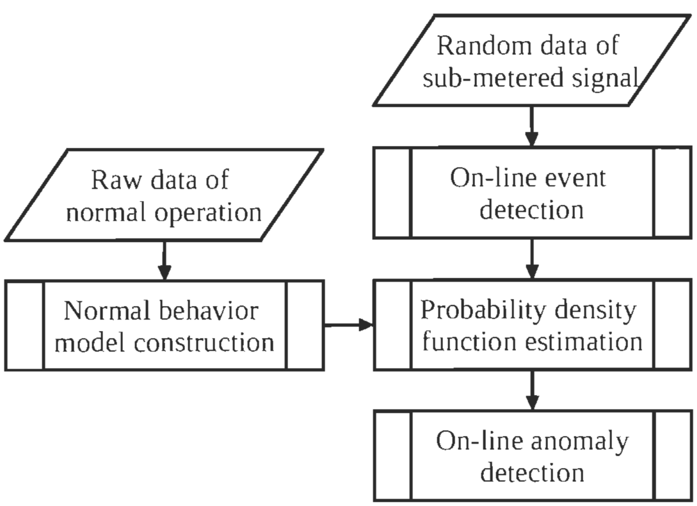

Figure 3-3 Block diagram of the on-line appliance-level anomaly detection system.

- Second, a semi-supervised anomaly detection method with low-complexity is developed to model the analytical factors. This model explains the normal behavior patterns by using Gaussian distribution functions that are applied to standard data through an off-line training phase. Consequently, it is employed to distinguish anomalies through probabilistic thresholds, determined based on Inverse Cumulative distributions of these functions.

- Third, an on-line technique is proposed to efficiently monitor the energy consumption and provide dynamic information for consecutive anomaly detection algorithms. This technique detects the operation cycles of the appliances candidate and estimates their PDF for anomaly based on the corresponding models, captured from the normal data. In fact, on-line data that comprises random (both regular and irregular) instances is exploited to evaluate the performance accuracy of the method by using a complete set of diagnostic tests.

3.4.3 Outcomes

The results of an exhaustive study about household appliance-level anomaly detection with the focus on finite-state energy-intensive loads particularly, refrigerators have brought about the below explanations.

- A useful understanding of the main opportunities and challenges of an operation-time anomaly detection by means of the analysis of energy and average power usages.

- Important notice of appliances type, operation behaviors, and analytical features to design an efficient method that can effectively estimate any deviation from normality.

- A critical proposition on an appropriate strategy to manage the time of anomaly detection and diagnosis decision with regard to differences between faulty and abnormal operations of an appliance.

The following study presents the aforementioned discussions in the context of residential appliances anomaly detection problem.

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A Practical Approach to Residential Appliances On-Line Anomaly Detection: A Case Study of Standard and Smart Refrigerators

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ABSTRACT Anomaly detection is a significant application of residential appliances load monitoring systems. As an essential prerequisite of load diagnosis services, anomaly detection is critical to energy saving and occupant comfort actualization. Notwithstanding, the investigation into diagnosis of household anomalous appliances has not been decently taken into consideration. This paper presents an extensive study about operation-time anomaly detection of household devices particularly, refrigerators, in terms of appliances candidate, by utilizing their energy consumption data. Energy as a quantitative property of electrical loads, is a reliable information for a robust diagnosis. Additionally, it is very practical since it is low-priced to measure and definite to interpret. Subsequently, an on-line anomaly detection approach is proposed to effectively determine the anomalous operation of the household appliances candidate. The proposed approach is capable of continuously monitoring energy consumption and providing dynamic information for anomaly detection algorithms. A machine learning-based technique is employed to construct efficient models of appliances normal behavior with application to operation-time anomaly detection. The performance of the suggested approach is evaluated through a set of diagnostic tests, by utilizing normal and anomalous data of targeted devices, measured by an acquisition system. In addition, a comparison analysis is provided in order to further examine the effectiveness of the developed mechanism by exploiting a public database. Moreover, this study elaborates sensible remarks on an effective management of anomaly detection and diagnosis decision phases, pivotal to correctly recognition of a faulty/abnormal operation. Indeed, through experimental results of case studies, this work assists in the development of a load monitoring and anomaly detection system with practical implementation.

INDEX TERMS Appliance load monitoring, on-line anomaly detection, energy consumption, load modeling, load diagnosis.

I. INTRODUCTION

With a 66.5 TWh electricity saving potential, residential sector becomes the world primary energy saving target among end-use sectors. The residential energy saving is reinforced by an inevitable increase in electricity prices and thus, customers affordability of spending on electricity consumption [1], [2]. Residential sector accounts for nearly a portion of 60% over 2017-25 and 70% over 2025-40 of building electricity demand rise. A significant share of this demand is due to the huge growth in the quantity and size of in-operation appliances in the projection period to 2040. Therefore, efficient operation and appropriate usage of household appliances play an important role in the achievement of energy saving targets [3], [4].

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A. HOUSEHOLD ANOMALOUS APPLIANCES

Household electrical appliances can undergo operational conditions that violate their normal operation. These abnormal conditions can be attributed to different causes that identify an appliance as anomalous. The consumption pattern of an anomalous appliance deviates from its expected behavior that complies with normality [5], [6]. From the perspective of normal behavior, both faulty operation due to electrical defects and abnormal usage due to customers' neglect can be defined as anomaly. Anomalous appliances can impede energy saving, reduce operation performance, and jeopardize safe operation. Accordingly, household appliances anomaly detection tools are highly useful for both customers to reduce the energy costs and system operator to enable energy efficiency improvements [7], [8]. Indeed, a reliable and efficient operation of household appliances, preserved by anomaly detection systems can increase energy saving up to 12% [9].

B. MOTIVATION AND CONTRIBUTION

Careful anomaly detection requires a framework that is capable of continuously monitoring appliances loads and providing their in-operation information for estimation algorithms. Accordingly, durable household load monitoring systems are emphasized as key enabler to designate such a structure [10], [11]. Although, these systems have been thoroughly probed from both intrusive and non-intrusive aspects, their anomaly detection capability has not been fairly taken into consideration. In terms of Non-Intrusive Load Monitoring (NILM), few studies have only investigated the proficiency of load disaggregation methods for anomaly detection [12], [13]. Furthermore, in [11], we have aimed to design a NILM system for diagnosis purposes. Nevertheless, state-of-the-art NILM methods are not adequate to provide efficient anomaly detection and thus, diagnosis services [11], [12]. In fact, anomaly in electrical appliances has a dynamic stochastic nature, for which providing a training class is a tedious task. The complication increases since a house consists of a range of appliances with completely different operating features due to their various manufactures/models. Notwithstanding a wide range of loads, the anomalous data is very limited that worsens the above problems [5], [14]. Therefore, an appliance-level anomaly detection approach is suggested that investigates the sub-metered data of a targeted-appliance in-depth and subsequently develops its efficient anomaly detection method. This concept is augmented by the inadequacy of aggregate-level anomaly detection techniques and advancements in cost-efficient smart plugs technology [15]. However, it has been almost ignored due to the interesting topic of a NILM with diagnosis abilities.

This paper provides a comprehensive study on household appliance-level anomaly detection by using energy consumption information of a smart and a standard refrigerator as appliances candidate. Particularly, it thoroughly examines anomalous behavior of the targeting loads that is ascribed to irregularity in their time of operation. Accordingly, this study proposes: 1) an on-line operation-time anomaly detection system with generalization ability that is dynamic to capture any deviation from normality in terms of faulty and abnormal operations; 2) a robust structure that is performed by a set of straightforward algorithms and requires minimum intrusion, least amount of information, and low resolution data (highly compatible with current metering technologies); 3) an efficient model of appliances normal behavior that is developed with practical application to diagnosis of an operation-time anomaly; 4) a highly accurate anomaly detection of appliances candidate, specifically periodic loads that consume a notable energy and are important for household energy saving; 5) the idea of diagnosis decision (as distinct from anomaly detection) that is resulted from an in-depth examination of operational conditions of anomalous appliances in terms of faulty or abnormal.

The rest of the paper is organized as follows. Section II provides a review of anomaly detection concept and its applications. Section III presents a thorough investigation into anomalous behavior of household appliances. Section IV describes the proposed approach through an in-depth discussion. Section V represents the results of the case studies and evaluates the method performance. Section VI discusses important remarks about anomaly detection and load diagnosis concepts in accordance with the provided analyses. The concluding remarks are presented in Section VII.

II. BACKGROUND

Anomaly detection plays a key role in load monitoring and predictive maintenance [16]. In the following, this concept is outlined from different perspectives and consequently discussed with regard to power system sectors, especially residential zone. Generally, an anomaly detection method is determined based on the nature of anomaly, which is categorized in three different classes. The simplest type, known as 'point anomaly', is a single data instance that is anomalous considering the rest of the data. The second class, expressed as 'contextual anomaly', refers to a deviation in a particular context regarding the structure of the data. For example, a temperature record of $-30°C$ during hot seasons can be anomalous however, in the context of cold seasons, this report can occur. The third category, defined as 'collective anomaly', implies a data portion that is collectively, not necessarily individually, anomalous [5]. For instance, a washing-machine program consists of individual events such as rinse, drain, and spin. Although these actions are individually normal, their occurrence in a wrong sequence can lead to a collective anomaly. From another viewpoint, anomaly detection methods are classified into 'data-driven' and 'model-based' practices, according to the way of acquiring a priori knowledge. In the former it is presumed that a notable amount of data is available, while in the latter some fundamental comprehension about the physics of the system is used to create a model [8]. From the standpoint of formulating an anomaly detection problem, machine-learning techniques have been widely utilized [17], [18]. In this regard, three different mechanisms can be defined, accounting for: 'Supervised', that is training a classifier by using labeled classes of both normal and anomalous data instances; 'Semi-supervised', that is training only by utilizing a labeled set of normal data; 'Unsupervised', that requires no training set since it groups the data under several clusters and defines dissimilar samples as anomaly. It should be noted that the supervised techniques simply consider an anomaly detection as a classification problem. On the other side, the semi-supervised methods are broadly exploited to separate outliers regarding normal samples (especially, when the classes are imbalance) [6]. The aforementioned perspectives can be further explored in the specified references.

The concept of anomaly detection has been broadly explored in different research domains such as computer network, image recognition, and machine operation [19]–[23]. In the context of power systems, this concept has been generally studied in the main grid sectors. Wang *et al.* have proposed a deep-learning based method for fault diagnosis in a power network by using the power flow information [24]. Hong *et al.* have analyzed an integrated anomaly detection system for network intrusion in the substations [25]. Shaw *et al* have focused on the anomaly detection of loads operation power in distribution systems [26]. They have employed a supervised method based on high sampling rate data of transient events to provide a classification between anomalous and normal instances. It should be noted that Shaw has considered a non-intrusive approach. In small-scale grids such as institutional sectors, Cui and Wang have explored the anomalous behavior of a school's electricity consumption by visualization of its related data [27]. They have utilized the half-hourly energy consumption data to assist with the challenging task of eyeballing of data for detecting anomalies.

At the household level, NILM ability to detect anomalies has recently drawn researchers' attention. The authors have previously investigated the NILM capability to provide diagnosis services [11]. Actually, in [11], we have aimed to enable NILM diagnosis capacity by designing a time-variant load modeling system. This framework exploits a recurrent pattern recognition and model construction mechanism to capture the dynamic of power consumption. Nevertheless, the essence of our analysis implies the difficulty of NILM methods to execute anomaly detection. Besides, other studies have mainly examined the proficiency of NILM methods for anomaly detection. Rashid *et al.* have evaluated the ability of household appliances load disaggregation techniques for anomaly detection [13]. Likewise, they have concluded that enhanced NILM algorithms are required to achieve such an ability. Furthermore, Rashid has made another similar study, where the inadequacy of NILM methods to provide anomaly detection has been inferred [12]. This inference has been made by manually inserting anomalies into limited number of appliances data from publicly available datasets. Therefore, their method of generating a synthetic anomalous data can point out further challenges of NILM in the presence of actual anomalies. Notwithstanding the above, in a prior study, Rashid *et al* have proposed a NILM system for anomaly detection [9]. Similarly, they have used publicly available databases such as ECO that can bring about further questions on their inference about anomalous appliances. For example, they have employed weather data to assist with their visualization of abnormal consumption. However, ECO dataset provides no information about the weather. Furthermore, their method, applied to power-level ratings of a set of known appliances, provides a low performance compared to the accuracy of current supervised NILM methods [11], [14]. This becomes more critical as they have not reported appliance-level anomaly detection results. Moreover, Jonetzko *et al* have suggested a non-intrusive load detection and diagnosis by exploiting high-frequency data with 4kHz sampling rate [28]. However, their study lacks to report any diagnosis results. Furthermore, due to utilizing a NILM method with a very low accuracy, they have reduced the dataset by removing the loads to increase the accuracy. Therefore, their method is not practical.

In fact, NILM barriers to a useful anomaly detection stimulates taking advantage of sub-metered measurements with regard to low-priced smart plugs technology. Accordingly, Ganu *et al* have provided a limited study about an appliance-level monitoring system [29]. They have utilized several electrical features to explain appliances behavior. However, their method can be simply described by a Hidden Markov Model (HMM) [30]–[33]. Although they have stated their method is unsupervised, it is likely to be semi-supervised due to a training phase with predefined parameters. Additionally, they have neither proposed an anomaly detection method nor presented numerical results. In [13], Rashid has also reported the anomaly detection based on sub-metered data. However, by utilizing a window length of one day, his analysis is more suitable for an off-line run. In addition, as demonstrated in this study (Section IV), a daily analysis is not efficient for appliances anomaly detection especially, periodic loads. It can notably restrict normal model construction, threshold definition, and on-line applications. Furthermore, such a window size necessitates a longer training phase. On the other side, Rashid's proposed technique has not been fairly examined since it has been mainly tested on one type of appliance anomaly (a refrigerator with continuously ON state). Considering the anomaly detection rules, it can be concluded that his method is only suited for significant anomalous events. This can be related to the choice of the window range that has limited a more precise anomaly detection. Moreover, the results have not been adequately evaluated due to a limited diagnostic test that can be also sensitive to imbalance classes. On the other hand, this comprehensive study contributes to appliance-level anomaly detection through actual experimentation with the aim of sensible applications. To the best of our knowledge, household appliance-level anomaly detection and diagnosis decision by exploiting sub-metered data has not been properly investigated. Such a concept allows an effective analysis of occupants usage and appliances operation behavior towards a careful anomaly detection. This is pivotal since the fidelity of customers and system operator to diagnosis feedback is highly influenced by its accuracy. It should be mentioned that available products, for which there is no valuable scientific report, does not normally aim

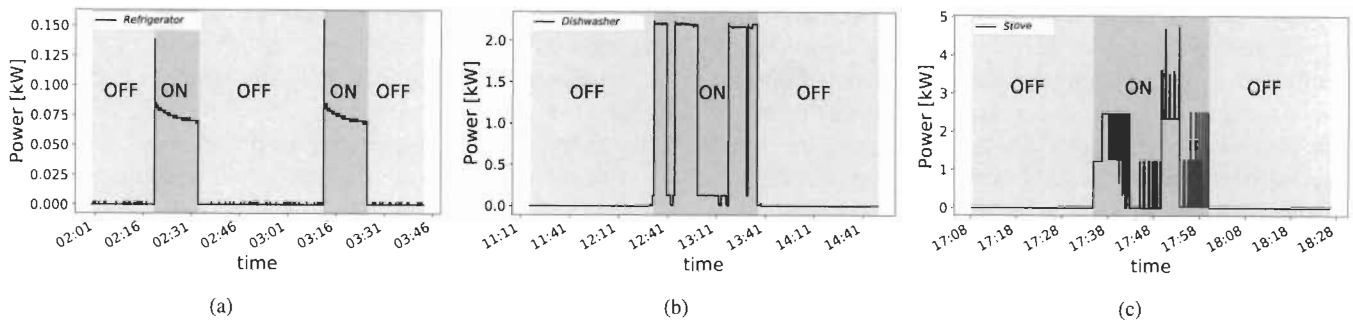


FIGURE 1. Two-state, (a) and multi-state, (b) and (c) household appliances can be expressed as two-state operation-time loads.

residential applications. Indeed, an extensive appliance-level study can aid in designing efficient aggregate-level methods.

III. PROBLEM DEFINITION OF APPLIANCE ANOMALY DETECTION

In fact, an effective strategy to approach an anomaly detection problem is to define its general features. Afterwards, the problem can be further elucidated with regard to case study and type of input information. In the context of a household, an anomaly detection problem can be characterized based on the following overviews.

A. OVERVIEW OF ANOMALY TYPE

Generally, household appliances demonstrate anomalous behaviors that can be attributed to either their operation-power or operation-time deviations. For two important reasons, the focal point of this analysis is the operation-time anomaly detection. First, irregular behavior of household appliances, especially with major power consumption (such as refrigerators, stoves, washing machines, and electric water heaters) is commonly implied by a faulty operation-time duration. Second, households electrical network has not been designed to capture this type of anomaly. Indeed, residential electric circuit is technically equipped to detect an operation-power anomaly within a normal consumption time rather than an operation-time anomaly with a normal power demand. According to the nature of anomaly, an operation-time anomaly can be expressed as a collective anomaly that occurs in the context of time [5]. For instance, a freezer with normal power demand that its ON state lasts for an unusually long time.

Moreover, the anomaly of household appliances is stochastic with a dynamic nature. Therefore, it is difficult to define an anomalous region that can be utilized to build a model. This issue deteriorates by knowing the fact that anomalous data instances are very limited and difficult to collect. Indeed, the number of abnormal occurrences are much less compared to normal ones, which causes highly imbalance classes [34]. Accordingly, semi-supervised machine learning methods are stimulated to deal with appliances anomaly detection due to the serious challenge of providing labeled class of anomalous data.

B. OVERVIEW OF APPLIANCE CANDIDATE

Household energy-intensive appliances are commonly finite-state loads that can be subject to malfunction at any operation state [35]. Nevertheless, from the perspective of operation-time anomaly detection, these appliances can be classified as two-state operation-time (ON/OFF) loads. This has been demonstrated for common household devices in Fig. 1. Such classification, as the essence of this study, facilitates providing a general anomaly detection method for finite-state loads.

In the context of a household, refrigerator is defined as a global energy-demanding appliance type. In both developing and advanced economies, refrigerators are among key factors for residential electricity consumption growth. They are the main purchased appliance with the increase of middle-income households in the world [3]. In fact, with more than two billion in-use numbers worldwide, refrigerators have a high penetration rate among main domestic equipment [36], [37]. On the other side, a refrigerator can undergo anomalous behaviors that can be attributed to different causes related to either a faulty operation or an abnormal usage. Despite other major domestic appliances, an anomalous refrigerator can bring about important energy saving issues since it is a permanently operating load with considerable energy consumption [38]. Although with most malfunctioning household devices, no (less) usage can avoid (reduce) anomaly impacts, this is not the case for refrigerators as permanent loads. Furthermore, an accurate anomaly detection of a refrigerator is complex since the causes of deviations from expected behavior are not always related to a failure. For example, the power profiles of an open-door refrigerator and a loaded one are very similar since both result in a lengthy operation time (discussed in Section IV). Indeed, the above remarks make refrigerators an appropriate candidate for an in-depth anomaly detection investigation with regard to two-sate operation-time appliances. It should be noted that this appliance has been also an interesting candidate for anomaly detection analysis in other researches [13], [29].

C. OVERVIEW OF SELECTED FEATURE

Our proposed appliance-level load monitoring and anomaly detection system utilizes the data of active power consumption with a one-minute sampling frequency, gathered by a sub-metered measurement system [39]. Therefore, it presents a data-driven approach for which, energy consumption is employed as the extracting feature to explore the anomaly in the targeted loads [8]. As a quantitative property of an electrical appliance, energy is a very practical feature for appliance-level anomaly detection systems. It is a reliable information for a robust diagnosis as a critical element of such systems. Energy is low-priced to measure and compatible with smart plug/meter structures. In fact, an energy-based anomaly detection method is easy to integrate with these structures since they both record energy consumption. Particularly, from the perspective of both customers and system operator, energy-based information is straightforward to comprehend since the electricity is delivered to customers in form of energy consumption [40].

According to the above analyses, an anomaly detection method is suggested for household two-state operation-time appliances that is semi-supervised, data-driven, and collective in the context of time. This work promotes an appliance-level anomaly detection problem in general rather than an appliance-specific one by using appropriate case studies. Even from the viewpoint of the latter, this study can be still general due to utilizing a basic method, a common electrical feature, and a low sampling rate (regarding energy-intensive loads) [41], [42]. Besides, the exploitation of sub-metered data is motivated by rapid influence of smart plug technologies. With the increasing significance of Internet of Things (IoT), smart plugs become beneficial for enabling smart appliances data connection [15], [43]. These appliances are not only equipped by an electricity connector but also a data connector according to digitalization aspect [3]. Smart plugs can provide a key opportunity for an extensive analysis of anomalous behaviors of major loads (specifically, refrigerators, washing machines, and air conditioners). Such an examination is essential to design efficient anomaly detection and diagnosis decision systems. It should be noted that current smart plugs are mostly normal operating systems and are not targeted to provide services for any specific type of appliances. Actually, future smart appliances can be themselves equipped with load monitoring and diagnosis services. As mentioned, this implies the practicality of the proposed approach since it can be integrated into different systems.

IV. METHODOLOGY

Our proposed mechanism for anomaly detection is the consequence of an exhaustive investigation into the behavior of the case studies based on their energy consumption. Accordingly, the following steps are executed to provide a thorough examination.

1- First, normal and anomalous behaviors of the appliances candidate (the standard and smart refrigerators) are explored through analyzing their specified electrical features, explained below.

2- Second, an on-line technique is proposed to efficiently monitor these electrical factors and provide dynamic information of targeted loads for consecutive anomaly detection algorithms.

3- Third, a semi-supervised anomaly detection method with low-complexity is developed that is capable of modeling the normal behavior of case studies and subsequently distinguishing their anomalous operation.

Moreover, useful remarks are elaborated as an explanation to the issues, discovered within our comprehensive analysis. As mentioned, in order to permit an actual implementation, the entire study is done by using the real data of our acquisition system.

A. COMPUTATION OF THE ANALYTICAL FEATURES

The behavior of the appliances candidate under different operation conditions is explored by the calculation of their energy consumption. These appliances consist of a standard single-door and a smart french-door refrigerator with completely different technical specifications. The energy consumption as the main analytical factor is computed through (1) [9],

$$u_w = \sum_{i=1}^{N_w} y_{k-i} \tag{1}$$

where k is the discrete time, during which a window size of w with N_w number of samples is captured for the energy analysis. y_k presents the active power demand at k, and u_w describes the energy consumption within w. Since energy, by definition, explains a constant power during a specific period of time, it is a convenient element to determine average power consumption within a targeted time duration. Therefore, average power usage, derived from energy based on (2), is another analytical factor that is employed,

$$\overline{u}_w = \frac{u_w}{N_w} \tag{2}$$

where $\overline{u}_w$ presents the average power use during time window w. Due to the accumulating nature of energy consumption, the average power quantity with no time dependency allows to recognize a stationary behavior and define the boundaries of variations over the time window of analysis. Furthermore, it eases the comparison between appliances different models of energy consumption behavior. As discussed in the following, this factor is critical for an accurate estimation of anomalous behavior of periodic loads such as refrigerators, freezers, and electric water heaters. This quantity can be easily converted to energy for a standard comprehension of electricity consumption in terms of kWh.

B. ANOMALY SCENARIOS

In fact, different conditions can cause the operation of a household refrigerator to deviate from normality. Therefore, four scenarios are considered to represent the common conditions that result in an anomalous behavior of a refrigerator. These scenarios are grouped into faulty and abnormal classes. Failure is attributed to a condition that cold air is constantly lost while abnormality is referred to as a situation that cold

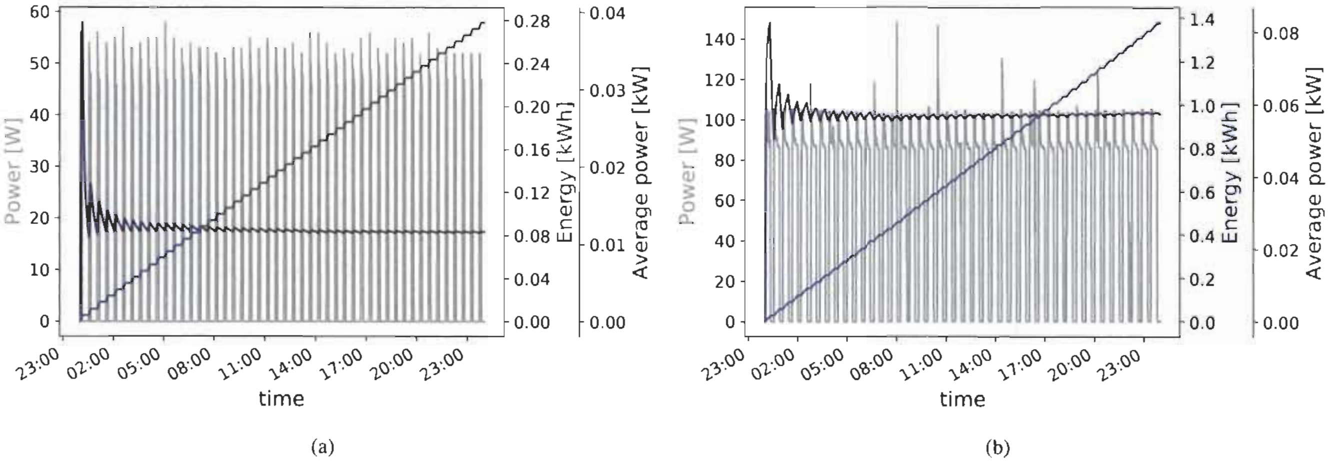


FIGURE 2. Daily energy and average power consumption of (a) standard and (b) smart refrigerators under normal operation.

air is finally kept inside by closing the door. The classes are numbered in an ascending order and explained as follow. The faulty class consists of cases 1: door not closed well; and 2: door with defective gasket. For the scenario 1, the door was left open at various angles for different time duration. For the scenario 2, the door gasket was deformed in different sides of the door for a long time to emulate a damaged one. The abnormal class comprises cases 3: door open/close overly; and 4: loaded refrigerator. For the scenarios 3, the door was overly open/close within several hours at different time of the day. For the scenario 4, the refrigerator was loaded with various amount of water at different temperature. Indeed, the variety of anomaly sources, which cause either a failure or an abnormality makes refrigerators a challenging load for a precise anomaly detection. This is not the case of other household energy demanding devices.

All aforementioned scenarios can lead to a notable waste of energy. Moreover, operating with dirty coils is another common condition that brings about an anomalous behavior. However, cleaning the coils, which requires customers' attention cannot make a considerable difference regrading the amount of energy usage of new refrigerators. Likewise, a freezer can be subject to the same scenarios and thus, the following examination can also provide valuable insights into the anomalous behavior of a freezer. It should be noted that refrigerators and freezers, recently along with air conditioners are the fundamental members of every single house [3], [44].

C. INVESTIGATION INTO NORMAL AND ANOMALOUS BEHAVIORS

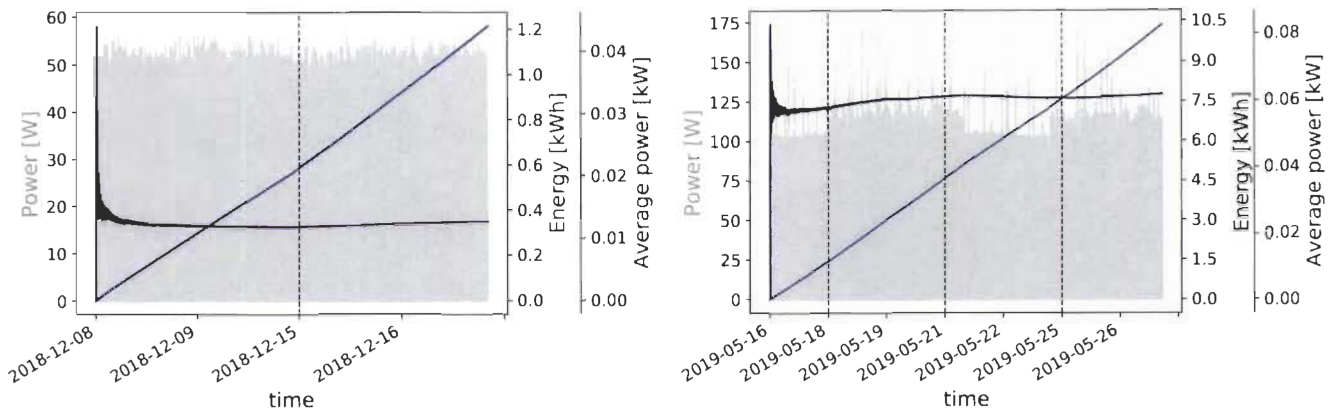
In our study, the anomalous behavior is deliberately induced by jeopardizing the normal operation based on the anomaly scenarios. Accordingly, an in-depth examination is provided in the following that outlines the key features of the proposed load monitoring and anomaly detection system. Furthermore, a detailed visualization is presented to assist with a clear comprehension. It should be mentioned that the following discussion is based on the exploration of the analytical factors, determined in Section IV.A.

1) NORMAL OPERATION OF APPLIANCES CANDIDATE

In order to capture the difference between normality and anomaly, the normal behavior is considered beforehand. Fig. 2 shows the daily energy and average power consumption for the normal operation of standard and smart refrigerators, respectively. It can be observed that the increase in energy consumption is consistently uniform. Furthermore, the average power usage demonstrates a stationary behavior within the time. More importantly, the consistency of energy growth and the stability of average power value is preserved over time. This has been demonstrated in Fig. 3, where the power profiles of non-consecutive days are coupled. It can be recognized that in concatenated days (black dashed lines), which are not successive, there is no inconsistency in the values of both examining factors. Consequently, the energy can be determined as a reliable criterion for normal behavior description due to the fact that the amount of energy use within normal operation cycles is almost identical. It is noted that the second factor is also stable since it has been computed by using the energy consumption. In addition, the modeling of energy and average power use of refrigerators and freezers is more efficient since their actual power consumption with notable transient is challenging to model (see Figs. 2 and 3).

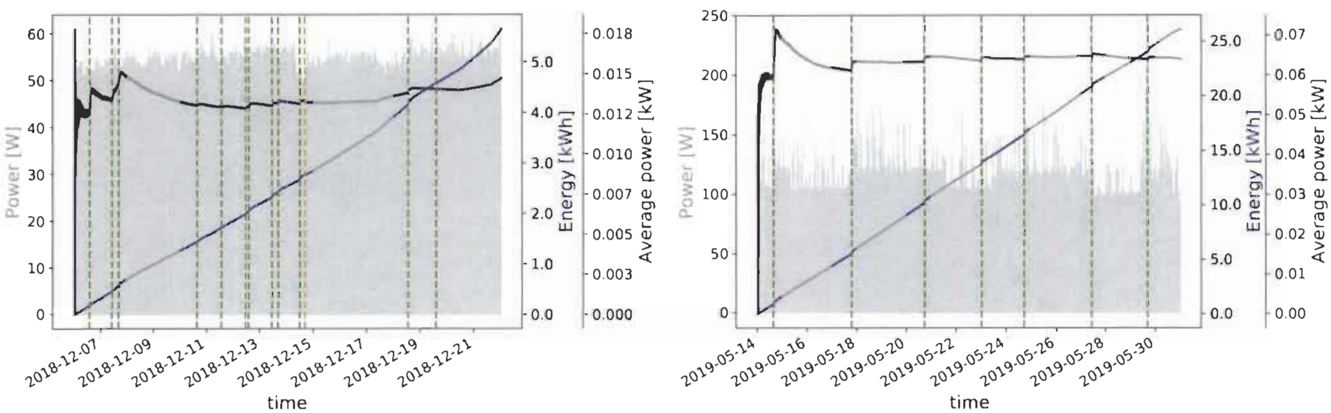
2) ANOMALOUS OPERATION OF APPLIANCES CANDIDATE

The anomaly scenarios have been executed during several days in order to provide sufficient evidences for the examination of their resultant irregular behavior. Accordingly, Fig. 4 illustrates the effect of anomaly scenarios on the energy and average power usage within a period of the experimentation. In this Figure, the green dashed lines illustrate the time in which an anomaly scenario has been experimented. Grey colors in-between energy and average power curves



(a) (b)

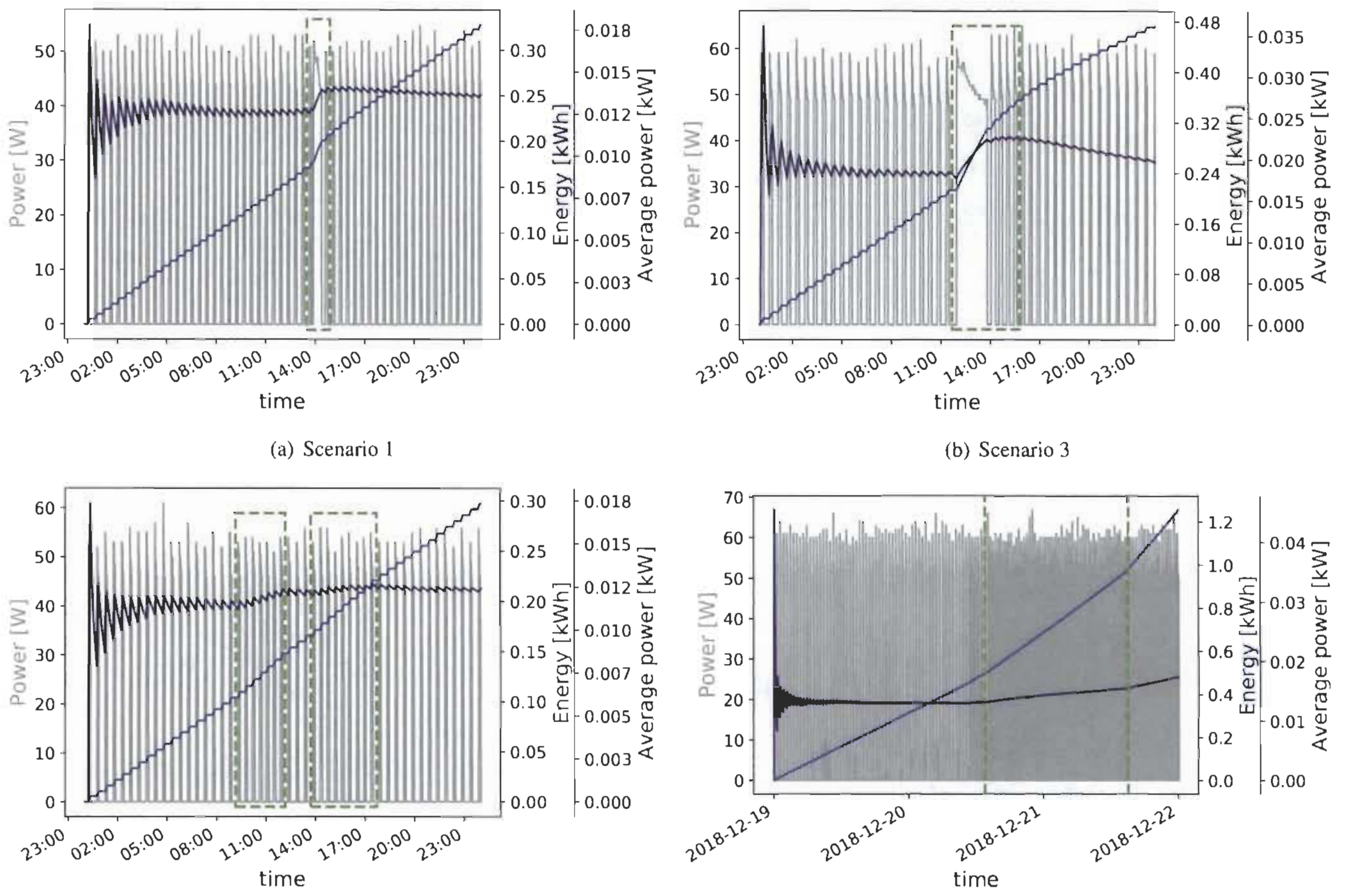
FIGURE 3. Consistent normality of energy and average power consumption of (a) standard and (b) smart refrigerators within non-sequential days under normal operation.



(a) (b)

FIGURE 4. Energy and average power consumption variations due to anomaly scenarios applied to (a) standard and (b) smart refrigerators. Each dashed line corresponds to the time of a specific anomaly test. Yellow dashed line presents an important case, explained in the text.

depict the days of normal operation with no anomaly test. It can be observed that all cases cause fluctuations in both the regular increase of energy demand and the regularity of average power use. These fluctuations occur exactly at the same time of the anomaly test that demonstrate the capability of the analytical factors for on-line applications. The variations can be acknowledged as a general alarm for an on-going anomaly when compared to the uniformity during normal operation. Generally, an anomalous behavior can be recognized by a sudden increase in both energy and average power consumption. Due to the normal behavior recovery, this increase is followed by a regular growth in the first factor and diminished steadily in the second one. The intensity of an anomaly depends on the extent of the induced scenario, for example the duration time of an open door. Nevertheless, no anomaly scenario has been exaggerated throughout the experiments. Even at the cost of a low accuracy, this study has avoided evident anomalies that can be easily captured. According to the operation condition that each scenario can cause, the following has been noticed. The scenarios 1 and 3 are more distinguishable. Scenario 2 is challenging to be differentiated from a normal condition, especially in a long term. These scenarios have been tested multiple times during every day of their experiment. Scenario 4 needs a longer period of time for the examination in comparison with other scenarios. Therefore, it has been executed within several days. With regard to the examined scenarios, there are relevant remarks that are discussed in details below through Fig. 5. In accordance with Fig. 4(a), there are other events that should be mentioned. The yellow dashed line with no scenario type is a noteworthy case that has been faced during the experiment. In fact, during the test days, a notable decrease in both factors has been experienced due to the loss of data in the acquisition system (zero consumption has been recorded in the database). However, in the lack of any clue about the source of such a behavior, it is yet difficult to attribute that to an anomalous refrigerator. The reason is that this event has caused a rapid reduction in the examining features (and not



(a) Scenario 1

(b) Scenario 3

(c) Scenario 2

(d) Scenario 4

FIGURE 5. A detailed demonstration of the energy and average power consumption fluctuations of the standard refrigerator due to the anomaly scenarios.

an increase based on the above explanation). Additionally, the unwanted growth during the normal days (after 2018-12-17) is due to deliberately decreasing the temperature set-point. Although this situation can be similar to an anomaly, the degree of a refrigerator is normally fixed by customers and its manipulation is not a common action.

Fig. 5 exemplifies the energy and average power demands behavior under each anomaly scenario. Although this is not the focus of this study, it can be observed that in a detailed view, the type of anomaly can be explored. Normally, the anomaly scenarios 1 and 3 lengthen the time duration of the refrigerator's ON operation within one to several cycles. Therefore, they provoke an immediate growth in both factors, as shown in Fig. 5(a) and 5(b). Actually, leaving the door open even slightly leads to a non-stoppable running that usually creates a cycle with long ON operation. Besides, the anomaly scenarios 2 and 4 boost the number of operation cycles. Consequently, they raise the slope of energy and level of average power consumption, as illustrated in Fig. 5(c) and 5(d). The scenario 4 should be studied in a longer period according to experimental observations that demonstrate gradual changes in the analytical factors under this case. During this scenario (Fig. 5(d)), it has been observed that the refrigerator operates with faster operation cycles (first slope change) and subsequently proceeds with longer ON operations (second slope change). In fact, door with defective gasket (scenario 4) is the only case that causes a permanent anomaly. These conditions can be generally encountered by other periodic-load appliances such as freezers.

According to the above analysis, it is deduced that the refrigerators are subject to an unexpected operation time growth in the presence of an anomaly. Likewise, this can be the situation for other energy-intensive appliances such as stove and electric water heaters that signifies our proposed approach to an operation-time anomaly detection system.

D. ANOMALY DETECTION TIME-WINDOW

An extensive examination of normal and anomalous behaviors of appliances candidate has been provided in the previous subsection. The main objective of such an analysis is to elaborates important remarks that can assist with the development of an efficient anomaly detection framework. In accordance with this investigation, it can be acknowledged that the time is a critical element in an energy-based anomaly detection. In fact, the time to capture an anomaly becomes crucial for two main reasons. First, the rapid response of energy-based

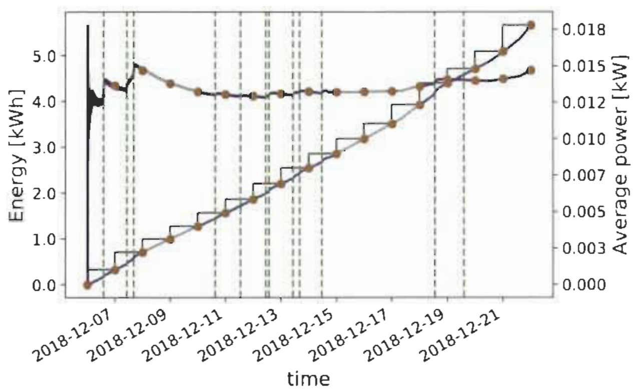


FIGURE 6. Daily energy and average power consumption of the standard refrigerator.

factors to an anomaly that promotes an actual on-line application. Second, the accumulative manner of energy usage and stationary behavior of average power use that necessitates a quick action. Actually, amassing the energy quantity over a notable time makes it difficult to distinguish a deviation in the consumption value. Likewise, the tendency to steady-state amount of average power demand causes a fluctuation to fade over a short time.

The time restriction to detect an abnormality can be explored by the analysis of both factors based on a daily time-window. Fig. 6 depicts the daily energy and average power demands during the same period as Fig. 4(a) for the standard refrigerator. For most of the scenarios, it can be observed that the amount of average power use at the end of a day (brown dots within the anomalous days) is lower than its value at the time that the anomaly has occurred. In fact, by the end of the day, this amount can be attributed to a normal condition instead of an anomalous event. On the other side, daily energy usage can be more useful because of its accumulating quality. Notwithstanding, it can be noted that anomalous and normal days produce similar step changes (brown dots within all the days) in their daily energy consumption. This situation becomes more challenging when the duration time (intensity) of an anomaly is not significant.

To more clarify, a Gaussian-based Kernel Density Estimation (KDE) based on (3) has been applied to daily energy and average power consumption data for the same duration as Fig. 6,

$$\hat{f}(x) = \frac{1}{N}\sum_{i=1}^{N}\mathcal{K}_h(x - x_i) \tag{3}$$

that for N number of data instances, x defines the discrete support, $\hat{f}(.)$ is the KDE function, $\mathcal{K}(.)$ presents a Gaussian Kernel, which is centered at each data sample x_i, and h specifies the bandwidth parameter. As a non-parametric method, KDE is a suitable choice for this analysis since the data stream includes the samples of anomalous days with completely random behavior. KDE is able to create an empirical probability density function (pdf) of every data point in order to estimate an unknown underlying distribution [11]. In order to reduce the complexity, a constant bandwidth with an empirical value has been chosen that has resulted in a better estimation through the experiments. Furthermore, the ability to offer an adequate description of normal behavior of energy-intensive appliances is the logic behind choosing a Gaussian Kernel [45].

Accordingly, Fig. 7 illustrates the results of KDE, applied to energy and average power consumption within a daily time-window. It can be seen that for the analytical factors of both case studies, a distinguishable region can be defined. For the standard refrigerator (Fig. 7(a) and 7(b)), this region deviates from the general region and can be highly related to anomalous events. Nevertheless, it contains very few data samples. For the smart refrigerator (Fig. 7(c) and 7(d)), the situation is the same however, the few instances in this region can be hardly associated to an anomalous operation due to their lower values (as discussed above). Therefore, for this case, the general region encompasses all anomalous samples. In fact, for the two refrigerators, the general region accounts for both normal and anomalous instances. It can be deduced that a daily analysis is inefficient to capture deviations from the common behavior that can be related to anomalous operation. Indeed, such an analysis is useful when a deviation is highly significant. Additionally, a daily examination can reduce the usability of the examining factors, considering the similarity between both distributions (locations of the samples). Consequently, the following remarks can be realized from the underlying distributions of data samples, captured through a daily time-window investigation.

1- Accumulating and stationary behaviors of energy and average power consumption over a day reduce the influence of a deviation (anomaly) over the normality.

2- Considering a specific amount of data, a daily time-window supplies the analysis with less number of samples and requires a lengthy duration of data acquisition [46]. Additionally, daily data can suppress detailed information that are valuable.

3- On a daily basis, defining a threshold to increase the number of correctly detected anomalies is challenging since in the general region, differentiating between normal and anomalous instances is more uncertain.

Regarding the KDE analysis, presented in Fig. 7, it should be mentioned that higher/lower values for bandwidth parameter do not improve the results. The former forms one region that means all data samples present the same behavior while the latter shapes several regions that means data instances offer different classes standing for multiple behaviors.

Generally, the time-window of the anomaly analysis can affect the influence degree of the analytical factors, the number of correctly detected deviations, and on-line implementations. Since an anomalous refrigerator demonstrates an unexpected periodic behavior, a cyclic time-window examination of energy and average power consumption is suggested. Fig. 8 demonstrates the KDE results of the cyclic investigation during the same period as daily analysis.

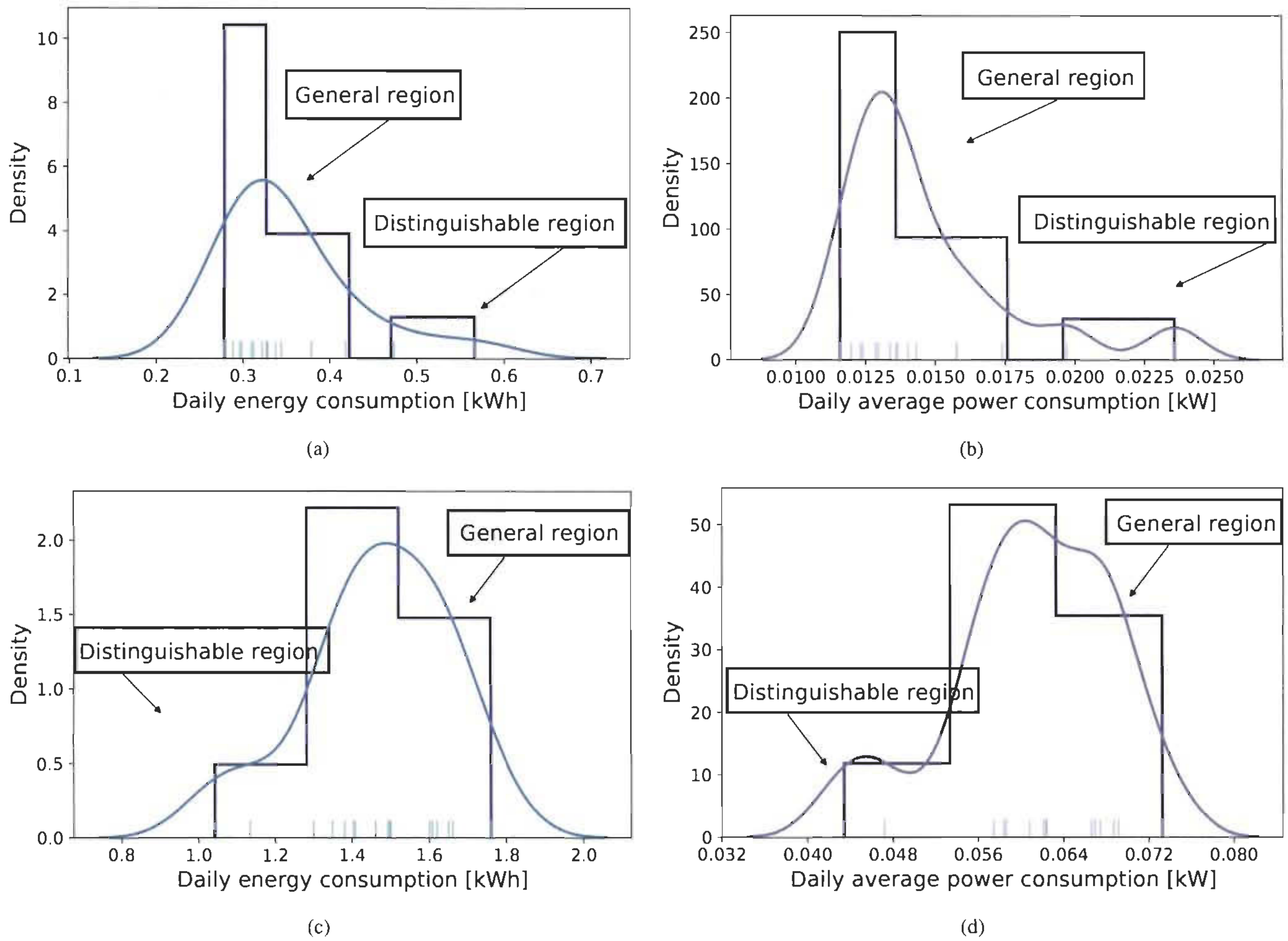


FIGURE 7. KDE of daily energy and average power consumption of standard (up) and smart (down) refrigerators.

The detection of operation cycle has been realized by constructing the operation-state (ON/OFF) sequence of the refrigerators based on a threshold. Consequently, a cycle is determined as an event that falls between two ON (or OFF) state transitions. As it can be observed in Fig. 8, a cyclic estimation results in distinguishable regions that can be distinctly segregated from general regions. Particularly, for the smart refrigerator, a distinguishable region has been created that in spite of its daily analysis, can be related to anomalous operations. Moreover, the cyclic analysis demonstrates that the analytical factors have different sensitivity with regard to resultant distributions (samples location) and the number of instances in the distinguishable regions. The samples of this region can be highly presented as anomaly since it is almost impossible to present them in a single category due to their random behavior. Subsequently, the general region as the only dominant class can be significantly associated with normality and in turn, assist with capturing an exact model of normal behavior. Therefore, it can be concluded that the capability of energy and average power consumption for anomaly detection remarkably improves by exploring the cyclic operation of the refrigerators (in comparison with the daily operation). Considering the remarks about the daily analysis, the following notes are emphasized for the cyclic one:

1- Analyzing the energy and average power consumption during an operation cycle can dramatically increase the impact of an anomaly on the normality. Therefore, this technique realizes a definite distinguishable region with larger instances of probable anomalies.

2- Knowing the fact that both examinations have been applied to the same amount of data, a time window with the length of a cycle provides the analysis with a substantial number of samples. Furthermore, it uncovers the detailed information to enable an explicit anomaly detection.

3- A cyclic investigation not only facilitates the choice of a threshold but also increases its flexibility due to the wide distribution of anomalous samples. The latter is significantly important since not all the anomalies require an (quick) action.

Moreover, a cycle-based mechanism can offer an on-line anomaly detection framework by enabling a faster estimation of analytical factors. It should be emphasized that in the cyclic analysis, the same bandwidth has been chosen to

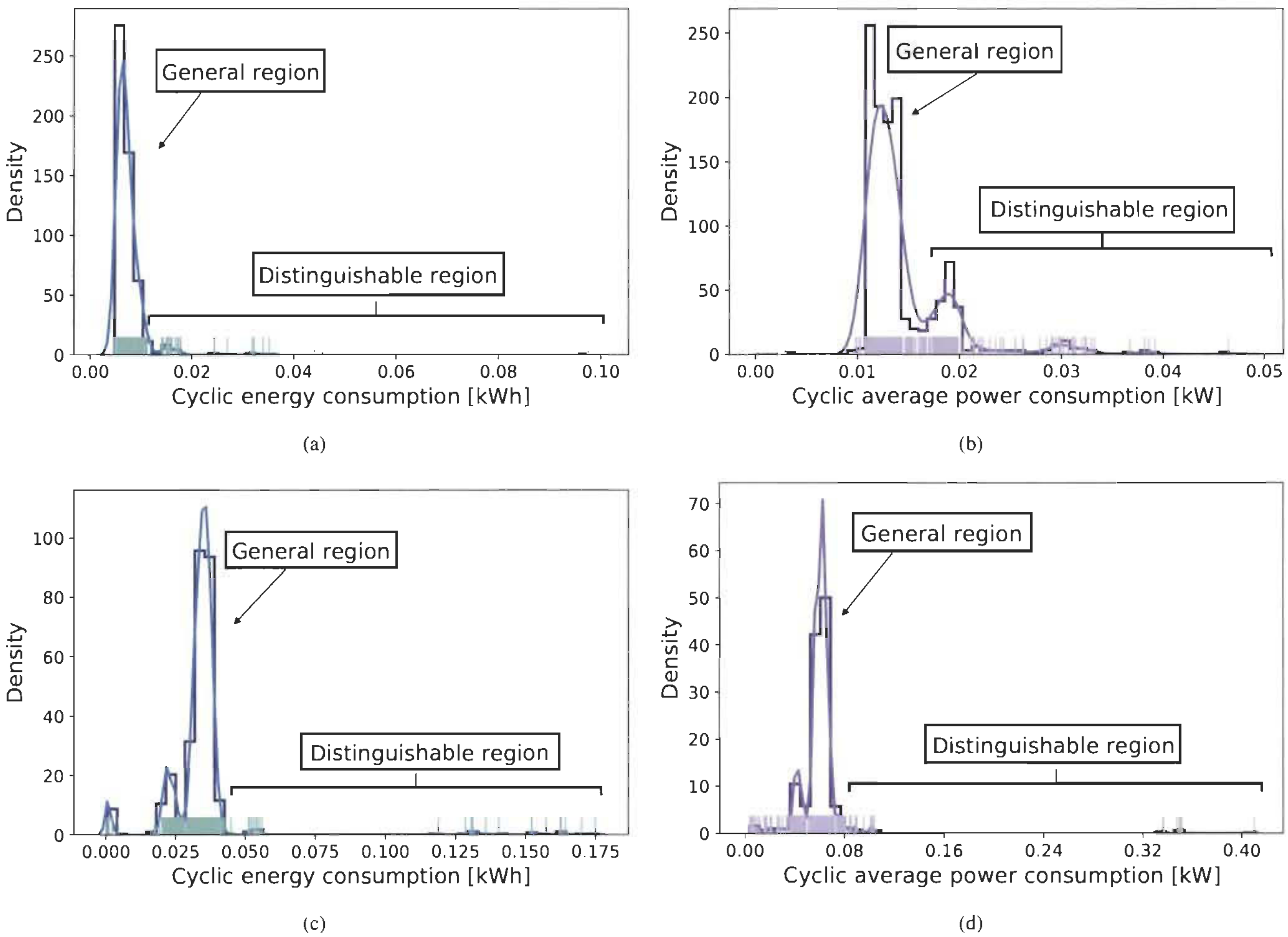


FIGURE 8. KDE of cyclic energy and average power consumption of standard (up) and smart (down) refrigerators.

provide acceptable results for KDE through all the cases. Regarding the completely different electrical features of the refrigerators, this can evidence the ability of such a mechanism to assist with the construction of general models of normal behavior. Therefore, a cyclic time-window is employed for the development of the proposed load monitoring and anomaly detection structure.

E. ANOMALY DETECTION FRAMEWORK

The comprehensive study, given above has provided a clear understanding about the refrigerators behavior from different viewpoints that can make an anomaly detection system feasible. Therefore, it is used to design both load monitoring and anomaly detection systems. In fact, the designated structure that is based on the operation cycles, consists of three procedures of normal behavior modeling, anomaly inference, and load monitoring.

As mentioned, the modeling process utilizes a semi-supervised machine learning method since it only constructs the model of the normal behavior. The cyclic energy and average power consumption are modeled in terms of Gaussian distributions $\mathcal{N}(.)$, due to the fact that a Gaussian Kernel has been able to provide a plausible explanation about these factors. Accordingly, the Gaussian parameters of each analytical factor are defined based on (4) and (5),

$$\mu = \frac{1}{C}\sum_{w=1}^{C} v_w \tag{4}$$

$$\sigma^2 = \frac{1}{C}\sum_{w=1}^{C} (v_w - \mu)^2 \tag{5}$$

that within C number of training cycles, μ and σ^2 presents the mean and variance of the modeling factor $v \in \{u, \overline{u}\}$. According to the related models, the anomaly is inferred through two steps. First, the probability density, $f(.)$ of energy and average power usage of a captured cycle is estimated by means of (6),

$$f(v \mid \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(v-\mu)^2}{2\sigma^2}\right) \tag{6}$$

Afterwards, the estimated densities are compared with their relevant thresholds to be identified as either normal or anomalous. These thresholds are computed by using the Inverse

Normal Distribution function of every Gaussian model. Accordingly, $\mu - \delta\sigma \leq T_v \leq \mu + \delta\sigma$ presents the lower and upper bounds of each threshold, T_v, respectively, where δ is defined based on three-sigma rule of thumb. As an essential prerequisite for the proposed anomaly detection structure, an on-line load monitoring framework is developed. This framework provides in-operation information of appliances candidate power consumption. It creates a data-frame according to the sampling time of data arrival. This data-frame, D is continuously expanded by storing the power consumption and the relevant state, z_k of every appliances candidate in order to capture its operation cycle. Consequently, the energy and average power consumption of the detected cycle is computed for model construction and anomaly inference phases. It is noted that the same state detection method, explained in the previous subsection is used for the on-line process. The above procedures result in an on-line load monitoring and anomaly detection system. In this system, an anomaly is detected by applying the diagnosis algorithm to the calculated analytical factors within a detected cycle, expressed by Algorithm 1.

Algorithm 1 On-Line Load Monitoring and Anomaly Detection

procedure $\mathcal{N}_v$ & T_v
  $D = \{\}$
  for (y_k, k) **do**
    # Step 1:
    define z_k
    $D = \{d_k \mid d_k = (y, z)_k\}$
    if $\Delta z_{k,k-1} = 1$ & $\Delta z_{k-N_w,k-N_w-1} = 1$ **then**
      # Step 2:
      calculate v_w ▷ According to (1) & (2)
      calculate f_{v_w} ▷ According to (6)
      # Step 3:
      if f_{v_w} *outof* T_v **then**
        $label_{v_w} \leftarrow Anomaly$
        $alarm_{v_w} \leftarrow ON$
      end if
    end if
    return *ON* alarms
  end for
end procedure

V. RESULT AND EVALUATION

The power consumption data of appliances candidate, measured by our acquisition system has been utilized to examine the proposed on-line anomaly detection approach. The developed structure is able to concurrently construct the model and estimate the anomaly. However, due to the importance of a robust detection, a practical model of normal behavior has to be ensured first. Accordingly, the normal behavior models of the refrigerators have been constructed within a time period of normal operation, in which no anomaly test has been executed. Nevertheless, the least amount of data has been exploited to build a feasible model and examine its performance with regard to a real-time implementation. It should be noted that normal condition presents a normal usage and does not mean a constantly close-door refrigerator. Subsequently, the most efficient model of each case study, captured by minimum amount of data has been employed to detect anomalous events, caused by different anomaly scenarios. Given the above, it can be comprehended that the algorithm is semi-supervised from the perspective of anomaly detection (due to the lack of an anomaly class) and supervised from the standpoint of model construction (due to utilizing a training phase). In fact, based on actual events that have been faced during the tests, a continuously unsupervised update of the normal model can be unreliable.

Besides, an appropriate diagnostic test is required to demonstrate the performance of the method. In fact, the accuracy metrics, reported in literature have been utilized to estimate either operation states or load profiles of a set of targeted appliances in the context of a load monitoring problem. However, in an anomaly detection system, the first target should be a correct diagnosis of the anomalous event. In such a system, the estimation of energy waste is also crucial, but this is not always the case. For example, informing the customers about an open-door refrigerator or left-on stove is sufficient since these incidents are not among poor behavioral consumption to be avoided by energy saving awareness. In this study, a set of diagnostic tests are employed that not only evaluate the general ability to detect an anomaly but also estimate the specific operation cycles that are affected by it. From the view point of the latter, the metrics are similar to those utilized in load monitoring studies for load profiling. Therefore, the accuracy metrics that are exploited to describe the results of anomaly detection are formulated as below,

$$Spe = \frac{tn}{tn + fp} \tag{7}$$

$$Acc = \frac{tp + tn}{tp + fp + tn + fn} \tag{8}$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \tag{9}$$

that *Spe*, *Acc*, and *F*1 stands for specificity, accuracy, and F_1-score, respectively. t_p describes true positives (number of correct detection of anomalous cycles), f_p explains false positives (number of false detection of a normal cycle as anomalous), t_n defines true negatives (number of true detection of normal cycles), and f_n expresses false negatives (number of false detection of an anomalous cycle as normal). Consequently, $precision = \frac{t_p}{t_p + f_p}$ and $recall = \frac{t_p}{t_p + f_n}$. The specificity metric determines the robustness of the model through its capability in correctly capturing the true normal events. This diagnostic test is essential for the performance evaluation of a household anomaly detection system due to the infrequent occurrence of anomalies in electrical appliances operation. It should be noted that specificity has not been necessitated for the evaluation of load monitoring processes. F_1-score is the harmonic mean of precision and recall that presents the

TABLE 1. Standard refrigerator modeling within normal operation cycles.

NoC		$\mathcal{N}(\mu, \sigma)$	Specificity(%)	F_1-score(%)	Accuracy(%)	E_A(%)
49	u	$(0.59, 0.034)10^{-2}$	72	57	77	150.34
	$\overline{u}$	$(11.97, 0.69)10^{-3}$	85	76	86	95.97
97	u	$(0.58, 0.029)10^{-2}$	69	54	74	155.24
	$\overline{u}$	$(11.74, 0.61)10^{-3}$	79	71	82	95.14
142	u	$(0.63, 0.072)10^{-2}$	98	92	98	103.70
	$\overline{u}$	$(12.24, 0.99)10^{-3}$	93	84	92	99.51
186	u	$(0.65, 0.081)10^{-2}$	97	84	95	106.9
	$\overline{u}$	$(12.59, 1.10)10^{-3}$	94	81	91	102.84

TABLE 2. Smart refrigerator modeling within normal operation cycles.

NoC		$\mathcal{N}(\mu, \sigma)$	Specificity(%)	F_1-score(%)	Accuracy(%)	E_A(%)
46	u	$(3.4, 0.8)10^{-2}$	90	83	92	107.64
	$\overline{u}$	$(6.4, 1.0)10^{-3}$	76	76	82	90.46
87	u	$(3.3, 0.07)10^{-2}$	98	98	99	101.32
	$\overline{u}$	$(5.9, 1.0)10^{-3}$	98	93	96	101.34

accuracy of the model to identify the anomalous events. Due to the sensitivity of F_1-score to imbalance classes, the accuracy score is also utilized to define the general correctness of the results. In addition, the ability to correctly estimate the amount of energy usage and average power consumption of anomalous cycles has been examined through (10),

$$E_A = 1 - \frac{\sum_{w=1}^{C} (\hat{x}_w - x_w)}{2\sum_{w=1}^{C} x_w} \tag{10}$$

where E_A is utilized for both the energy and average power estimations. $\hat{x}_w$ and x_w are estimated and actual quantities of analytical factors within C cycles, respectively. In fact, E_A is applied to the estimated energy and average power of detected anomalous cycles during testing phase of each scenario. In order to report the overestimation, this metric has been revised to consider the real value of the nominator since the absolute value can only interpret the underestimation. Actually, the performance evaluation of an anomaly detection procedure is not simple. It should be noticed that the load monitoring process has been mainly reported in literature by using F_1-score and energy estimation (based on the absolute value). Although our ambition is to uncover an anomaly, a severe evaluation process has been used that examines both state detection and load profiling abilities.

Accordingly, Table 1 presents the results of normal behavior modeling of standard refrigerator. The model has been examined over an overall set of anomalous events based on the four predefined scenarios. In such manner, the model is not tuned to a specific scenario since anomaly is a general description, given to any kind of deviation from normality. In addition, Table 2 describes the modeling procedure of the smart refrigerator. The term 'NoC' explains the Number of Cycles with normal behavior that have been utilized to construct the model. The resultant Gaussian models of both analytical factors have been also presented. It can be noticed that their parameters vary through normal operation cycles. Although low variations demonstrate the stability of normality to rapidly extract an efficient model, it is observed that they can notably influence a precise anomaly detection. It should be mentioned that the energy has been presented based on kWh and averaged over the number of samples of the detected cycle to compute the average power (kW).

The minimum number of the cycles to capture an efficient model of the standard refrigerator is 142 that accounts for around three days of normal operation. The tests have shown that enlarging the modeling period cannot yield a notable improvement. Besides, as it can be noticed, this number of cycles has provided highly accurate results. On the other side, 87 number of normal operation cycles, associated with around two days, is the least number to extract an effective normal model of smart refrigerator. The corresponding model has provided a remarkable anomaly detection performance as well. It should be highlighted that the less modeling period of the smart refrigerator is due to a more sensitive response to any deviation, and not because of a more stabilized normal behavior. Nevertheless, the minimum time to ensure a standard model is completely depend on the user behavior. For example, a refrigerator with less utilization requires more time to offer an acceptable model since the boundaries of normality have to be defined with respect to customers' usage behavior.

Accordingly, the performance of the on-line load monitoring and anomaly detection method to capture a specific anomaly scenario is estimated based on the efficient models. In fact, the feasible model of normal behavior can provide a valid estimation of the anomaly scenarios. Accordingly, Table 3 expresses the on-line anomaly detection results of the four scenarios for the standard refrigerator. It can be observed

TABLE 3. On-line load monitoring and anomaly detection of test scenarios applied to standard refrigerator.

Scenario		Specificity(%)	F_1-score(%)	Accuracy(%)	E_A(%)
1	u	99	86	99	106.57
	$\overline{u}$	97	80	97	93.01
2	u	-	-	-	-
	$\overline{u}$	100	63	87	103.33
3	u	98	75	98	110.28
	$\overline{u}$	89	50	89	92.59
4	u	100	96	96	96.65
	$\overline{u}$	97	99	99	98.83

TABLE 4. On-line load monitoring and anomaly detection of test scenarios applied to smart refrigerator.

Scenario		Specificity(%)	F_1-score(%)	Accuracy(%)	E_A(%)
1	u	99	91	99	99.35
	$\overline{u}$	100	80	98	91.93
Blackout	u	96	98	98	100.79
	$\overline{u}$	100	87	89	105.43

that the efficient model is highly accurate to distinguish anomaly from normality for any type of deviation (caused by different scenarios). Furthermore, it is able to estimate the deviating consumption in the analytical factors with high performance. Although the energy consumption factor has not been able to recognize the scenario 2, this has not been interpreted as a failure. This scenario mainly influences the duration time of OFF state rather than ON. Actually, overly opening/closing of the door has caused the standard refrigerator to operate with less OFF periods. However, the energy consumption (as it can be noticed) computes the amount of energy demand due to an ON operation condition. Therefore, the average power consumption has been also considered as a complementary factor to uncover the OFF-state deviation and its impact on the whole cycle due to an abnormal operation. In addition, this factor is useful in explaining the anomalous behavior corresponding to scenario 4 since this scenario influences both operation states. Furthermore, the average power consumption can reflect the abnormality due to the loss of data as it interprets that as OFF period. Such a situation has been encountered during our tests (yellow dashed line in Fig. 4(a)).

Besides, Table 4 reports the on-line anomaly detection results of the efficient model of the smart refrigerator. The anomaly detection algorithm has been tested for the smart refrigerator after several months of its effective model construction. It can be observed that the model is notably correct in detecting the anomalous behavior related to the scenario 1. The high accuracy of diagnostic tests particularly, specificity score after a long time demonstrates the stability of the normal operation and in turn the robustness of the model. During the anomaly tests of smart refrigerator, we have suddenly experienced a rapid blackout. Afterwards, a permanent anomalous behavior has been warned by our on-line anomaly detection algorithm, while no anomaly test has been proceeded. Therefore, the power consumption behavior of the refrigerator has been observed. As illustrated in Fig. 9, the blackout event (grey dashed line) has totally disrupted the normal behavior of the refrigerator. Nevertheless, this unexpected event has not been considered as a disturbance. On the contrary, this advantageous incident has enabled a critical evaluation of the on-line anomaly detection system within an actual failure. Therefore, the blackout has been examined in terms of a scenario. The results indicate that the method has a high accuracy to detect this event especially, regarding the energy consumption factor. Furthermore, both factors are very efficient to estimate the deviations due to the blackout experience. The continuation of this incident is comparable with the behavior of the scenario 4. The blackout examination has been done during several days before stopping the system for required inspections. However, this has not brought a major concern with the tests of scenarios 2 and 3 (considering the benefits of such a realistic incident) since these scenarios are very similar in behavior to scenarios 4 and 1, respectively. In addition, they are not classified as an actual failure, as mentioned in Section IV.

Moreover, the proposed approach is compared with the method that has been studied by Rashid in [13] using REFIT database [47]. In this study, discussed in Section II, a similar analysis is provided that has been applied to freezer as another household periodic appliance. Rashid has tested his technique within a period of three months. However, our suggested method is implemented for almost all the data (one year) of the freezers in the same homes of REFIT database to present an extensive examination. Accordingly, Table 5 presents the comparison results. Likewise, 'NoC' presents the number of cycles that have been used to construct an efficient model. In [13], the training duration is one month however, in our

TABLE 5. Accuracy results of the proposed approach in comparison with the method in [13], tested on REFIT database.

REFIT	NoC	Accuracy (%)	On-line anomaly detection system				Rashid [13]
			3 months	6 months	9 months	12 months	3 months
Home 10	76	Precision	100	83	95	95	100
		Recall	100	100	100	99	100
		F_1-score	100	91	97	97	100
Home 16	96	Precision	92	81	78	80	90
		Recall	92	91	91	90	90
		F_1-score	92	86	84	85	90
Home 18	156	Precision	100	92	92	88	100
		Recall	100	100	100	93	70
		F_1-score	100	96	96	90	80
Home 20	99	Precision	71	77	76	78	100
		Recall	100	100	100	100	60
		F_1-score	83	87	87	88	70

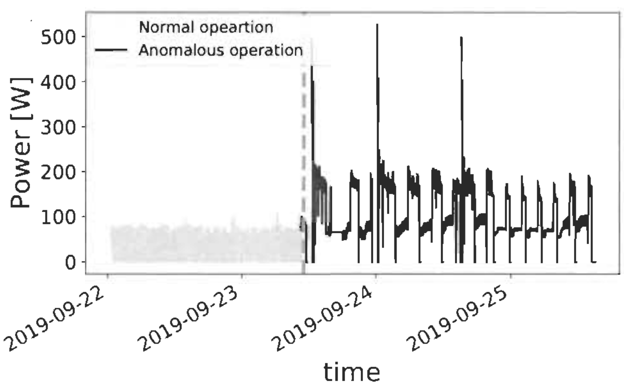


FIGURE 9. The blackout event during the anomaly experiment on the smart refrigerator; the gray dashed line indicates the approximate time of the event occurrence.

case, this period is maximum 156 cycles (House 18) that accounts for around 7 days. Besides, Rashid has used two factors to decide an anomaly. Therefore, in order to provide an equal analysis, a deviation has been identified as anomaly that has been detected by both analytical features (energy and average power usage). It should be detailed that one of the analytical factors, used in [13] is the daily number of operation cycles. Nevertheless, our actual experiments demonstrate that this factor varies in a sensible way (useful for anomaly detection), mostly when an intense anomaly occurs. The reason is that a noticeable anomaly can generally result in a lengthy operation time and thus, decrease the daily amount of cycles. The comparison has been made based on the same accuracy metrics. The results of the proposed approach have been reported every three months. It can be seen that the suggested method is notably accurate within the entire test period. This high performance that has been maintained over a long time validates the robustness of the designed framework. Particularly, the outcomes are very competitive regarding a three-month comparison (the test duration in [13]). In fact, except for precision score in House 20, the on-line anomaly detection system is more accurate in all the cases. It can be realized that the developed structure is also effective for other periodic appliances. Indeed, the correct results that have been obtained from other case studies (homes in REFIT dataset) demonstrate the generalization capability of the proposed mechanism.

It is worth to point out that author of REFIT database has declared the information of anomalous events [47]. However, by a complete examination of this dataset, it has been realized that there are other operation deviations and loss of data (similar to reported ones) that have not been mentioned. It should be noted that the comparison analysis has been concluded by considering these additional instances. Nevertheless, this has not notably influenced the results, compared to an assessment without such samples due to their few numbers. Actually, the evaluation of both conditions has resulted in the same accuracy during three months and an insignificant difference only after a long period (9 months and more).

VI. DISCUSSION

In accordance with the above results and analyses of the proposed on-line appliance-level load monitoring and anomaly detection system, the following remarks should be discussed.

1- Although this work has focused on household periodic energy-intensive appliances as the case studies, its approach to anomaly detection is general. It has explored the operation-time anomaly concept that can be applied to other types of appliances. Furthermore, the method has utilized a common electrical feature in a low-sampling frequency that is compatible with current metering technologies and household energy-demanding devices. Employing normal electrical properties is critical to develop a general method, however appliances, particularly refrigerators can still have basic signatures that are notably different.

2- Since the study has been done in the appliance-level with sub-metered information, a highly accurate anomaly detection process has been intended. Therefore, a careful set of diagnostic scores has been utilized to examine the results. These accuracy rules are very precise such a way that their estimation of the outcomes can be attributed to load profiling rather than load diagnosis. From the standpoint of anomaly detection, the proposed method is totally capable of recognizing any anomalous behavior particularly, the ones that are considered as failure.

3- A supervised machine learning algorithm that signifies an off-line process has been employed to create the normal behavior models of the appliances candidate. A supervised method can facilitate capturing an efficient model that can handle both the stochastic nature of anomalous behavior of an appliance and the variation of its normal electrical characteristics (due to different reasons, e.g. aging). In fact, ensuring effective models of loads regular patterns, which guarantees customers' fidelity to warning alarms, is pivotal for a usable anomaly detection system. Although an on-line model construction, mainly aimed by unsupervised methods, is interesting, the stationary behavior of household energy-intensive appliances reduce its necessity. The concern with an unsupervised modeling of normal behavior increases considering an anomaly detection system with poor performance. For example, it is possible that such a system considers the abnormal behavior of a refrigerator with defective gasket as normal (due to the continuation of this kind of anomaly).

4- It is advised that a load monitoring and diagnosis system should be capable of early diagnosis. Nevertheless, our thorough study has demonstrated that the term 'early' (one can read real-time) depends on different matters, characterized as below:

- The application: Among the chosen scenarios, two of them are actually a failure. However, all scenarios have been detected as anomaly since they cause similar variations on normal energy consumption. This is due to the operation-time anomaly nature rather than the model inadequacy. Therefore, an early detection should be defined based on the applications that generally account for fault (scenarios 1 and 4) and over-usage (scenarios 2 and 3) diagnosis.
- The time: Scenarios 1 and 4 express a failure. Although the energy consumption is rapidly influenced by an anomaly, these cases require different time period to ensure an abnormality. The anomaly detection system is quick to capture scenario 1 however, it needs more time to recognize scenario 4 (in our case more than one day). Furthermore, the time can affect the recognition of an irregular behavior due to aging problems. Subsequently, a load diagnosis system is real-time with respect to the type of anomaly that it seeks to detect.
- The urgency: Generally, an operation-time anomaly of a refrigerator can be dealt with as an energy saving issue. However, this is not the case for a stove that has been left ON. In fact, an anomalous stove can cause a dangerous situation instead of energy waste. Consequently, the early diagnosis should favor the type of a targeting appliance.

Accordingly, a load monitoring and diagnosis system is suggested that its diagnosis phase accounts for two separated steps of anomaly detection and diagnosis decision. As a result, the term 'early' can be an appropriate fit for the former. The anomaly detection should capture a deviation when it occurs (on-line distinguishability) and the diagnosis decision should confirm a malfunction when there is adequate evidences (e.g. continuation of a deviation).

VII. CONCLUSION

Anomaly detection is a significant application of load monitoring systems. In the residential sector, this application can assist with different kind of energy saving awareness. Due to the inadequacies related to an aggregate-level implementation from one side and future low-priced smart plugs from the other side, an appliance-level anomaly detection aspect is reinforced. Accordingly, this paper has provided an exhaustive investigation into different aspects of an appliance-level anomaly detection with regard to household energy-intensive appliances. As a result, an on-line load monitoring and anomaly detection approach has been proposed that is capable of expeditiously capturing any operation-time abnormality. The proposed approach has been examined by implementing an actual framework. This framework applies the suggested design to the measured data of a set of appliances candidate. These appliances account for a standard and a smart refrigerator with different electrical characteristics. Refrigerators are important household finite-state loads that can bring about challenging anomalous behaviors. Therefore, they are a suitable case study for anomaly detection of household energy-expensive loads. The results based on careful diagnostic tests have demonstrated the high performance of the proposed method. Furthermore, the efficiency of the suggested technique has been demonstrated through an extensive comparison analysis. Moreover, the utilization of a group of straightforward algorithms, examined on a physical operating system, has validated the pertinence of the developed structure to smart meters/plugs systems. With regard to the case studies, this analysis has elaborated important remarks on a full appliance-level load monitoring in terms of a system capable of continuous load observation, anomaly detection, and diagnosis decision.

REFERENCES

[1] R. Cary and D. Benton, "Creating a market for electricity savings: Paying for energy efficiency through the energy bill," Green Alliance, London, U.K., Tech. Rep., 2012. [Online]. Available: http://assets.wwf.org.uk
[2] World Energy Council. (2016). Eenegy Efficiency : A Straight Path Towards Energy Sustainability. [Online]. Available: https://www.worldenergy.org
[3] International Energy Agency. (2018). *World Energy Outlook 2018: The Future is Electrifying*. [Online]. Available: https://www.iea.org
[4] C. G. Mattera, M. Jradi, and H. R. Shaker, "Online energy simulator for building fault detection and diagnostics using dynamic energy performance model," *Int. J. Low-Carbon Technol.*, vol. 13, no. 3, pp. 231–239, Sep. 2018.
[5] V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detection," *ACM Computing Surv.*, vol. 41, no. 3, pp. 1–58, 2009, doi: 10.1145/1541880.1541882.

[6] L. F. Maimo, A. L. P. Gomez, F. J. G. Clemente, M. G. Perez, and G. M. Perez, "A self-adaptive deep learning-based system for anomaly detection in 5G networks," *IEEE Access*, vol. 6, pp. 7700–7712, 2018.

[7] E. Mills, "Building commissioning: A golden opportunity for reducing energy costs and greenhouse gas emissions in the united states," *Energy Efficiency*, vol. 4, no. 2, pp. 145–173, May 2011.

[8] Q. Yang, "Model-based and data driven fault diagnosis methods with applications to process monitoring," Ph.D. dissertation, Dept. Elect. Eng. Comput. Sci., Case Western Reserve Univ., Cleveland, OH, USA, 2004.

[9] H. Rashid, N. Batra, and P. Singh, "Rimor: Towards identifying anomalous appliances in buildings," in *Proc. 5th Conf. Syst. Built Environ.*, New York, NY, USA, 2018, pp. 33–42.

[10] S. S. Hosseini, K. Agbossou, S. Kelouwani, and A. Cardenas, "Non-intrusive load monitoring through home energy management systems: A comprehensive review," *Renew. Sustain. Energy Rev.*, vol. 79, pp. 1266–1274, Nov. 2017.

[11] S. S. Hosseini, S. Kelouwani, K. Agbossou, A. Cardenas, and N. Henao, "Adaptive on-line unsupervised appliance modeling for autonomous household database construction," *Int. J. Electr. Power Energy Syst.*, vol. 112, pp. 156–168, Nov. 2019.

[12] H. Rashid, P. Singh, V. Stankovic, and L. Stankovic, "Can non-intrusive load monitoring be used for identifying an appliance's anomalous behaviour?" *Appl. Energy*, vol. 238, pp. 796–805, Mar. 2019.

[13] H. Rashid, V. Stankovic, L. Stankovic, and P. Singh, "Evaluation of non-intrusive load monitoring algorithms for appliance-level anomaly detection," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2019, pp. 8325–8329.

[14] S. Makonin, F. Popowich, I. V. Bajic, B. Gill, and L. Bartram, "Exploiting HMM sparsity to perform online real-time nonintrusive load monitoring," *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2575–2585, Nov. 2016.

[15] S. Zhai, Z. Wang, X. Yan, and G. He, "Appliance flexibility analysis considering user behavior in home energy management system using smart plugs," *IEEE Trans. Ind. Electron.*, vol. 66, no. 2, pp. 1391–1401, Feb. 2019.

[16] I. Ullah, F. Yang, R. Khan, L. Liu, H. Yang, B. Gao, and K. Sun, "Predictive maintenance of power substation equipment by infrared thermography using a machine-learning approach," *Energies*, vol. 10, no. 12, p. 1987, 2017.

[17] Y. Jia, L. Sun, and H. Teng, "A comparison study of hidden Markov model and particle filtering method: Application to fault diagnosis for gearbox," in *Proc. IEEE Prognostics Syst. Health Manage. Conf. (PHM-Beijing)*, May 2012, pp. 1–7.

[18] R. Granell, C. J. Axon, and D. C. H. Wallom, "Impacts of raw data temporal resolution using selected clustering methods on residential electricity load profiles," *IEEE Trans. Power Syst.*, vol. 30, no. 6, pp. 3217–3224, Nov. 2015.

[19] S. Chang, B. Du, and L. Zhang, "BASO: A background-anomaly component projection and separation optimized filter for anomaly detection in hyperspectral images," *IEEE Trans. Geosci. Remote Sens.*, vol. 56, no. 7, pp. 3747–3761, Jul. 2018.

[20] K. Xie, X. Li, X. Wang, G. Xie, J. Wen, J. Cao, and D. Zhang, "Fast tensor factorization for accurate Internet anomaly detection," *IEEE/ACM Trans. Netw.*, vol. 25, no. 6, pp. 3794–3807, Dec. 2017.

[21] M. Khatua, S. H. Safavi, and N.-M. Cheung, "Detection of Internet traffic anomalies using sparse Laplacian component analysis," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2017, pp. 1–6.

[22] N. A. Aditiya, M. R. Dharmawan, Z. Darojah, and D. R. Sanggar, "Fault diagnosis system of rotating machines using hidden Markov model (HMM)," in *Proc. Int. Electron. Symp. Knowl. Creation Intell. Comput. (IES-KCIC)*, Sep. 2017, pp. 177–181.

[23] Tushar, S. Pandey, A. K. Srivastava, P. Markham, and M. Patel, "Online estimation of steady-state load models considering data anomalies," *IEEE Trans. Ind. Appl.*, vol. 54, no. 1, pp. 712–721, Jan. 2018.

[24] S. Wang, S. Fan, J. Chen, X. Liu, B. Hao, and J. Yu, "Deep-learning based fault diagnosis using computer-visualised power flow," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 17, pp. 3985–3992, Sep. 2018.

[25] J. Hong, C.-C. Liu, and M. Govindarasu, "Integrated anomaly detection for cyber security of the substations," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1643–1653, Jul. 2014.

[26] S. R. Shaw, S. B. Leeb, L. K. Norford, and R. W. Cox, "Nonintrusive load monitoring and diagnostics in power systems," *IEEE Trans. Instrum. Meas.*, vol. 57, no. 7, pp. 1445–1454, Jul. 2008.

[27] W. Cui and H. Wang, "Anomaly detection and visualization of school electricity consumption data," in *Proc. IEEE 2nd Int. Conf. Big Data Anal. (ICBDA)*, Mar. 2017, pp. 606–611.

[28] R. Jonetzko, M. Detzler, K.-U. Gollmer, A. Guldner, M. Huber, R. Michels, and S. Naumann, "High frequency non-intrusive electric device detection and diagnosis," in *Proc. 4th Int. Conf. Smart Cities Green ICT Syst.*, 2015, pp. 209–216.

[29] T. Ganu, D. Rahayu, D. P. Seetharam, R. Kunnath, A. P. Kumar, V. Arya, S. A. Husain, and S. Kalyanaraman, "SocketWatch: An autonomous appliance monitoring system," in *Proc. IEEE Int. Conf. Pervas. Comput. Commun. (PerCom)*, Mar. 2014, pp. 38–43.

[30] L. Abdesselam and C. Guy, "Diagnosis of induction machine by time frequency representation and hidden Markov modelling," in *Proc. IEEE Int. Symp. Diag. for Electric Mach., Power Electron. Drives*, Sep. 2007, pp. 272–276.

[31] F. Salfner and M. Malek, "Using hidden semi-Markov models for effective online failure prediction," in *Proc. 26th IEEE Int. Symp. Reliable Distrib. Syst. (SRDS)*, Oct. 2007, pp. 161–174.

[32] J.-S. Huang and P.-J. Zhang, "Fault diagnosis for diesel engines based on discrete hidden Markov model," in *Proc. 2nd Int. Conf. Intell. Comput. Technol. Autom.*, vol. 2, Oct. 2009, pp. 513–516.

[33] Q. Zeng, J. Qiu, and G. Liu, "Application of hidden semi-Markov models based on wavelet correlation feature scale entropy in equipment degradation state recognition," in *Proc. 7th World Congr. Intell. Control Autom.*, Jun. 2008, pp. 269–273.

[34] Y. Wang, S. Sun, and J. Zhong, "An ensemble anomaly detection with imbalanced data based on robot vision," *Int. J. Robot. Automat.*, vol. 31, no. 2, pp. 77–83, 2016.

[35] N. Henao, K. Agbossou, S. Kelouwani, S. Hosseini, and M. Fournier, "Power estimation of multiple two-state loads using a probabilistic non-intrusive approach," *Energies*, vol. 11, no. 1, p. 88, 2018.

[36] J. Belman-Flores, D. Pardo-Cely, M. Gómez-Martínez, I. Hernández-Pérez, D. Rodríguez-Valderrama, and Y. Heredia-Aricapa, "Thermal and energy evaluation of a domestic refrigerator under the influence of the thermal load," *Energies*, vol. 12, no. 3, p. 400, 2019.

[37] H. Nakagami, C. Murakoshi, and Y. Iwafune, "International comparison of household energy consumption and its indicator," in *Proc. ACEEE Summer Study Energy Efficiency Buildings*, no. 8, 2008, pp. 214–224.

[38] F. G. Arroyo-Cabañas, J. E. Aguillón-Martínez, J. J. Ambríz-García, and G. Canizal, "Electric energy saving potential by substitution of domestic refrigerators in Mexico," *Energy Policy*, vol. 37, no. 11, pp. 4737–4742, Nov. 2009.

[39] C. Guzman, L. Rueda, G. Romero, S. Biscans, K. Agbossou, and A. Cardenas, "Enabling winter behavior analysis on electrically heated residential buildings by smart sub-metering," in *Proc. IEEE Int. Conf. Ind. Technol. (ICIT)*, Feb. 2018, pp. 1213–1218.

[40] C. Guzman, K. Agbossou, and A. Cardenas, "Real-time emulation of residential buildings by hardware solution of multi-layer model," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 4037–4047, Jul. 2019.

[41] S. Hosseini, N. Henao, S. Kelouwani, K. Agbossou, and A. Cardenas, "A study on Markovian and deep learning based architectures for household appliance-level load modeling and recognition," in *Proc. IEEE 28th Int. Symp. Ind. Electron. (ISIE)*, Jun. 2019, pp. 35–40.

[42] K. Carrie Armel, A. Gupta, G. Shrimali, and A. Albert, "Is disaggregation the holy grail of energy efficiency? The case of electricity," *Energy Policy*, vol. 52, pp. 213–234, Jan. 2013.

[43] N. K. Suryadevara and G. R. Biswal, "Smart plugs: Paradigms and applications in the smart City-and-Smart grid," *Energies*, vol. 12, no. 10, p. 1957, 2019.

[44] *The Role of Refrigeration in the Economy*. 29th Informatory Note Refrigeration Technol., International Institute of Refrigeration, Paris, France, 2015.

[45] H. Kim, M. Marwah, M. Arlitt, G. Lyon, and J. Han, "Unsupervised disaggregation of low frequency power measurements," in *Proc. SIAM Int. Conf. Data Mining*, Apr. 2011, pp. 747–758.

[46] S. Hosseini, S. Kelouwani, K. Agbossou, A. Cardenas, and N. Henao, "A semi-synthetic dataset development tool for household energy consumption analysis," in *Proc. IEEE Int. Conf. Ind. Technol. (ICIT)*, Mar. 2017, pp. 564–569.

[47] D. Murray, L. Stankovic, and V. Stankovic, "An electrical load measurements dataset of united kingdom households from a two-year longitudinal study," *Sci. Data*, vol. 4, no. 1, Dec. 2017, Art. no. 160122.

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Chapter 4 - Discussion and future opportunities

4.1 Introduction

The foundation of this section is built on the extensive studies that have been provided for every targeted element, essential for a successful ALMD system. Accordingly, we attempt to describe the statement of each problem and the proposition. Furthermore, the reasons that have motivated every suggestion are detailed, through which the future studies according to further potentials are defined. In fact, the subsequent explanations have their roots in the last section (preceding the conclusion) of each paper, where the outcomes of the corresponding research have been explicitly discussed.

4.2 Data generation approach

Indeed, the proficiency of the database, resulted in a data generator is the consequence of a larger investigation into the other aspects of NILM systems rather than their mathematical process. These perspectives that mainly focus on the essential prerequisite and the practical outcomes can remarkably affect the algorithms. These two phases can define the methods, influence the accuracy, and manage the desires. In our NILM exercise, failing to obtain a publicly available database with appropriate information of ESH and EWH has evidenced the importance of sufficient data. Furthermore, this exercise has bolstered the significance of intended applications as the outcomes of the load monitoring system. Nevertheless, the studies have almost neglected the investigation into these two factors. Efficient literature has mainly studied the load disaggregation process of NILM. Accordingly, the examination of essential necessities and actual services have drawn our interest. As parts of the same process, these aspects should be analyzed in accordance with each other. Indeed, the key perception that outlines the feature space completely depends on the implementations. Taking an achievable NILM into consideration, our extensive exploration of the above factors has resulted in a system with significant properties, described below. The appeal for realizing such characteristics can bring about effective research studies to make NILM concept feasible.

- Appliances candidate: The information space of NILM should target household appliances with specific features that can assist with both energy savings and grid services. Considering the former, it should include appliances candidate that are among major consumption devices. Regarding the latter, it should consider the energy-intensive applicants that their electricity usage has the potential of being delayed. In fact, household energy-expensive loads particularly, thermostatic ones have the capability of being deferred within their operation time. Deferrable Appliances (DA) are important for both demand and supply sides' scenarios. These appliances are capable of providing grid services without jeopardizing the quality and reliability of their primary function according to users' comfort level and satisfaction. For example, in Quebec, Canada, DA, including ESH and EWH reveals a great potential for energy savings and power grid facilities due to their large electricity consumption. In the US, the same scenario can be realized for space cooling devices as the household dominant energy consumers specifically, during hot seasons. Therefore, a NILM system with such an oriented information space can enable sensible applications, concerned by both customers and system operator. This concept is signified by the fact that the current feature space of NILM is too complex.

- Enhanced applications: Small-scale renewable energy resources are an inevitable factor of the residential sectors of future power grids. Accordingly, a NILM system should contribute to the effective utilization of renewable resources. NILM methods can be enhanced to exploit DA capacity as Medium Energy Storage (MES) systems to expedite more integration of small-scale renewables. Such a perspective gives more importance to the utilization of DA capacities in the demand side. Besides, the future power systems have an undeniable load that is presented by Plug-in Electric Vehicles (PEV). PEV as residential new energy-intensive loads can cause remarkable opportunities and challenges to NILM implementations. Not only these devices must be considered in the information space of any practical NILM, but also their effective communication with DA has to be managed. The latter can lead to advanced applications of energy savings and grid services in the context of NILM. Consequently, the new players in both supply and demand sides can bring about interesting matters for NILM to be handled by its further improvements.

- Real-time aspect: NILM should realize a real-time structure as an essential quality of future power networks under the smart grid paradigm. The real-time computing is a pivotal aspect of any ALM systems that must be defined based on the applications (which describe the deadlines). This aspect is highlighted considering the new movement of technology towards different designs such as the Internet of Things (IoT) environment, which can provide enhanced communication among utilities, manufactures, and customers. It should be mentioned that the traditional NILM concept with a huge complicated space of data, slow analytical process, and long computational time is usually an offline system. In fact, a real-time capability can result in a NILM structure under which, improved utilization of the aforementioned components (DA, PEV, and renewables) become possible. This structure can establish a beneficial communication between both customers, who look for incentives by participating in grid services and the system operator, who seeks effective management of the power network. Subsequently, NILM enhanced exercises should be enabled in a real-time design in order to be considered practical.

- Synthetic data generation: Particularly, the examination of data efficiency for NILM practices with regard to specific cases of Quebec has motivated the idea of data generation tool. Accordingly, the simulation structure, used to generate the synthetic data can realize new research chances that are not only restricted to NILM exercises. It can enable the exploration of the relationship between appliances' energy consumption and occupants' behavior, household thermal interactions, as well as environmental conditions. In addition, this tool can assist with the study of time-extended HEMS scenarios. Furthermore, it can facilitate the correlation analysis between household occupants behavior and outdoor temperature fluctuations based on electricity consumption patterns. Generally, synthetic data generation tools are signified due to the limited availability of detailed measured data and costly manner of collecting it in large amounts. Therefore, these tools can benefit researchers with a variety of demand-side studies before actual experimentation.

Indeed, an advanced framework can provide solutions to the standstill of the conventional NILM. Such an architecture can offer new opportunities for both customers and utilities by preparing real-time facilities to monitor, identify, and control DA and PEV. The real-time management of these energy-expensive devices lies in the first place of near-future applications of NILM. Furthermore, the integration of small-scale renewable energy resources can truly alter the role of buildings in distribution systems and transfer them to micro-grid systems that can independently operate through HEMS. In fact, an advanced NILM can create new research fields in the area of household ALM systems in the near future.

4.3 Household database construction approach

For many years, load disaggregation has been the focal point of NILM studies. Therefore, we have proposed to examine the essentials of a NILM system for diagnosis purposes. Accordingly, a time-variant load modeling system (regarding the dynamic of power consumption) has been designed with two important abilities, accounting for the recognition of new appliances and the continuous learning of their parameters. Indeed, these abilities are important for diagnosis systems that require knowledge about new loads and their standard behavior. Consequently, our approach has been presented in terms of household appliances database construction. In fact, this approach has not been adequately explored, especially in the scale of our analysis. Our database constructor has utilized different mechanisms for each of which, further independent studies can be provided. These techniques and the interesting matters that they can bring about are discussed in the following.

- Prior knowledge: Notwithstanding its complexity, our load modeling structure employs an unsupervised machine-learning method. In fact, we have developed a fully unsupervised procedure that is capable of operating with less or no initial information. To the best of our knowledge, unsupervised disaggregation studies have mostly considered a set of initializations by use of general information. However, due to the diversity of household appliances in types and brands, providing an appropriate space of information is difficult. Therefore, the studies have considered more specific information that has resulted in a likely semi-supervised analysis (an unsupervised method with specific priors). Nevertheless, the importance of general information cannot be denied, since an analysis with no prior knowledge can decline an accurate interpretation of the results and decrease the performance of the modeling process. However, we propose to study the effect of this information in the level of housing stock in order to enhance their application by reducing uncertainties.

- Adaptive on-line framework: Our time-varying analysis with less/no prior knowledge has suggested the exploitation of an adaptive structure to extract the preserved sequential information in the data. As a result, by using the adaptive estimation of appliances' model parameters, we have developed a thoroughly adaptable procedure for an effective interpretation of their behavior. Adaptive learning can effectively assist with research studies that aim for an enhanced appliance load modeling system. Due to deterministic trends of a locally non-stationary electric signal, an adaptable method can be used as the key answer to a gradually model generation concept. Adaptive learning can facilitate the interpretability of underlying information and applicability of generated models. Additionally, an adaptable design can expedite the load modeling and disaggregation by achieving a structure capable of differentiating between the processes required for novel emerging events and existing instances. Therefore, it can make an on-line model learning concept feasible. Additionally, an adaptable procedure can be utilized for load behavior analysis by supervising the operation trends of the uncovered models. Moreover, an adaptive modeling structure using household general information can aid with diagnosis purposes. It can facilitate the recognition of the model parameters with unusual values by searching the data of past normal operation. An adaptable modeling system can be also considered for the reduction of customers intervention who has no expertise in appliances' operation.

- Pattern recognition promise: Our extensive method consists of two main processes of 'model detection and supervision' as well as 'model construction and revision'. The first process has been achieved by developing a pattern recognition system. This system has not been necessitated in load disaggregation studies however, it can promote interesting analyses. The common facet of pattern recognition and load disaggregation methods is the load identification. Nevertheless, the former does not undergo the energy estimation phase. Therefore, household appliances' pattern recognition can be used to form an accelerated load identification system with actual on-line implementations. It can create a concept of NILM that does not require a disaggregator. This concept can be presented as a system that intends to detect the load patterns and monitor their recurrence. Therefore, it can be utilized to study the appliances' consumption behavior and their relationship with occupants' activities. A recurrent pattern recognition structure can be exploited to study the operation schedules of household devices. Furthermore, this structure can be employed to recognize the type of a pattern (regular or periodic) by continuous monitoring of its value and operating time. Therefore, it can provide hypotheses about the type of a load, for example multi-state devices that are normally regular loads (their operation period is limited). Moreover, such a framework can be exploited for load diagnosis services since it can capture the deviations in patterns' recurrence. Besides, a recurrent pattern recognition system requires further studies to define appropriate accuracy metrics for its performance evaluation. In fact, this framework can be improved from different perspectives such as mathematical methods, intended applications, and evaluating processes.

- Human intervention: Our proposed structure employs an unsupervised method with no prior knowledge and thus, notably reduces human involvement in the set-up phase. Reducing human intervention requires a disaggregator with no/less training. However, due to supervised and semi-supervised nature of the most load disaggregation methods, human efforts have been required in initial model construction. In addition, we have tackled the idea of appliances' automatic labeling by using an unsupervised load profiling in order to reduce final human intervention. This concept has been mainly ignored in previous studies. In fact, the necessity for human supervision is a fundamental issue of NILM systems. This issue can hinder real on-line applications, reduce customer motivations after purchase, and influence the usability of manufactured products. By constructing a household database, we have intended the maximum reduction of human intervention. Nevertheless, removing human involvement from both initial and final load identification phases needs further investigations.

– Appliances candidate: Targeting multi-state appliances can be regarded as another important improvement to our developed database constructor. Indeed, the proposed structure constructs the models of finite-state load appliances in terms of two-state loads. Therefore, it cannot identify multi-state appliances and thus, it considers them as a composition of two-state loads. To be precise, due to the unsupervised nature of our method that uses no prior knowledge about household appliances, it is almost impossible to identify multi-state appliances. These appliances have a wide-range of power consumption based on their brand, for example washing machines. Therefore, their recognition requires general information or sub-metered data compared to periodic loads with similar power consumption such as refrigerator. As a matter of fact, these types of appliances have been always a challenging object for enhanced NILM mechanisms. Moreover, it should be mentioned that our proposed method has difficulty with modeling of identical loads particularly, refrigerators and freezers. As mentioned, the analysis of periodic loads with highly similar power consumption values is a fundamental issue of NILM studies, which has been mainly ignored (see our study in Appendix A). One reason can be attributed to the fact that this is a rear scenario among popular datasets that have been utilized for load disaggregation, such as REDD (Reference Energy Disaggregation Data Set). Indeed, this type of NILM issue requires its specific context of analysis since it may necessitate the utilization of more complex algorithms.

Correspondingly, the aforementioned items have provided important matters for future studies through discussing the characteristics of our household database construction framework in accordance with the lack of current NILM systems.

4.4 On-line anomaly detection approach

Recently, enabling the diagnosis capability of ALM systems has received attention among the researches. Therefore, different studies have been conducted to evaluate NILM abilities specifically, load disaggregation engines for this purpose. Nevertheless, the current disaggregators are not adequate to provide satisfying load diagnosis services. Accordingly, an appliance-level anomaly detection approach has been intended during our investigation into ALMD systems. This approach has resulted in developing an on-line operation-time load monitoring and anomaly detection system as another proposition of this study. This system that has been evaluated through a set of actual scenarios by utilizing real measured data can be discussed from different standpoints as below.

- Generalization ability: Although the proposed system has focused on one type of household energy-intensive appliance as the case study, its approach to the anomaly detection is general. The reason is that this system has explored the operation-time anomaly concept, which can be applied to other types of appliances. In fact, an operation-power anomaly detection can be not easily generalized due to the variety of electrical characteristics of household appliances for which, a specific power consumption model is required. Nevertheless, this is not the case for the operation-time anomaly since the time of energy consumption is general information of electrical loads. From this standpoint, all energy-intensive devices can be generalized to two-state loads. Therefore, a general operation-time anomaly detection method can be promoted for such household devices. Furthermore, the generalization capability of the method can be actually experimented since it has utilized a common electrical feature in a low-sampling frequency that is compatible with current metering technologies. In fact, such an analysis can be recommended for further examination of the proposed anomaly detection structure.

- Diagnostic test: Our analysis has utilized a careful set of diagnostic scores to examine the results. The reason for such an intensive evaluation is the utilization of sub-metered information that has necessitated intending a highly accurate anomaly detection process. Nevertheless, defining effective diagnostic tests to be utilized for household appliances anomaly detection studies require further examinations. This does not necessarily mean complex evaluation methods. Although our diagnostic metrics are very precise such a way that their estimation of the outcomes can be attributed to load profiling, the practical scores can be simple to only examine the detection abilities. In fact, different accuracy metrics are required to evaluate energy estimation and load diagnosis capabilities of an ALM system. The former assesses the correct interpretation of a load's power profile. Since the main goal of an anomaly detection system is to diagnose the failure, the latter only requires to estimate the correct inference of anomaly during its occurrence. Nevertheless, this process becomes complicated since not all the deviations in an appliance's standard behavior can be attributed to a failure. Therefore, different matters should be considered while designing the diagnostic scores for an anomaly detection system.

– Standard behavior modeling aspect: In our analysis, a supervised machine learning algorithm has been employed to create the normal behavior models of the appliances candidate. In fact, it is suggested that further improvements to standard behavior modeling of household devices should be done based on (semi-)supervised methods. A supervised algorithm can facilitate capturing an efficient model that can handle both the stochastic nature of anomalous behavior of an appliance and the variation of its normal electric characteristics (due to different reasons, e.g. aging). Indeed, ensuring an effective model of regular load's pattern that guarantees customers' fidelity to warning alarms is a pivotal feature of a usable anomaly detection system. A supervised modeling is mainly an off-line process however, the anomaly detection procedure is performed in an on-line manner. Although an on-line model construction, mainly aimed by unsupervised methods, is interesting, the stationary behavior of household energy-intensive appliances reduce its necessity. The concern with an unsupervised modeling of normal behavior increases since it is possible that an anomaly detection system with poor performance considers (for example) the abnormal behavior of a refrigerator with a defective gasket as normal (due to the continuation of such an anomaly).

– Diagnosis decision: It is advised that a load monitoring and diagnosis system should be capable of early diagnosis. Nevertheless, our thorough study has demonstrated that the term ‘early’ (one can read real-time) depends on different matters that demand more exploration.

- The application: In our experimentation, among the chosen scenarios, two of them are actually failure. However, all scenarios have been detected as anomaly since they cause similar variations on normal energy consumption. This is due to the operation-time anomaly nature rather than the model inadequacy. Therefore, early detection should be defined based on different applications that generally account for fault and over-usage diagnosis.
- The time: Although the energy consumption is rapidly influenced by an anomaly, various cases require different time period to ensure an abnormality. Furthermore, the time can matter the recognition of irregular behavior due to aging problems. Subsequently, the real-time applicability of a load diagnosis system should be analyzed with respect to the type of anomaly that it seeks to detect.
- The urgency: Generally, an operation-time anomaly of a refrigerator can be dealt with as an energy-saving issue. However, this is not the case for a stove that has been left at ON-state. In fact, an anomalous stove can cause a dangerous situation instead of energy waste. Consequently, the early diagnosis should favor the type of targeting appliance. This concern leads to an appliance-specific load diagnosis idea that can stimulate more individual analyses of operation behavior of household appliances.

Accordingly, a load monitoring and diagnosis system is suggested that its diagnosis phase accounts for two separate steps of anomaly detection and diagnosis decision. As a result, the term ‘early’ can be an appropriate fit for the former. The anomaly detection should capture a deviation when it occurs (on-line distinguishability) and the diagnosis decision should confirm a malfunction when there are adequate evidences (e.g. continuation of a deviation). This should be the outlook for additional studies on full anomaly detection and load diagnosis systems. In these studies, the stability of the proposed systems along with their sensibility to different sources of noise should be analyzed with regard to practical implementations.

This exhaustive discussion has detailed the properties of the proposed approaches throughout this document. The essence of this discussion is based on the outcomes that have been already outlined in every corresponding article. Nevertheless, it has been mostly upgraded to a viewpoint that is more general with regard to future research studies. Accordingly, the roots of this study are concluded in the next section to finalize our efforts to analyze household ALMD systems.

Chapter 5 - Conclusions

This study has focused on an investigation into household ALMD systems. By means of an extensive exploration of these systems, three main problems have been determined for further improvements. This research has attempted to define these problems with regard to other significant matters of ALMD concept that have not been decently taken into account. As a result, three main issues of the proficiency of the database, the feasibility of ALM, and the diagnosis of anomalous appliances have been examined that consequently led to the suggestions of this essay. These suggestions account for the data generation tool, the household database construction, and the on-line anomaly detection. The proposed approaches have been detailed in three separate studies (articles) for each of which, the following conclusions are provided.

- Data generation approach: In the first study, the problem of the lack of proficient data for energy-expensive appliances in exceptional regions, particularly Quebec have been focused. Accordingly, a semi-synthetic data generation tool has been developed. Generally, this tool utilizes the operation schedules and electrical characteristics of real appliances, located in a house to create the power profiles of other devices for which, there is no actual data. The results have shown that the proposed approach is capable of effectively capturing the probabilistic schedules of appliances and constructing the targeted devices' power profiles. By using the individual loads' information, the suggested tool can yield to aggregated load profiles' creation for different HEMS scenarios. As stated, the first research has also conducted a thorough study on major issues required to achieve an actual NILM. The promise of NILM approach eases the effective cooperation among stakeholders in the electrical energy industry in the context of HEMS and gives a new force to inevitable move toward the SH concept. Apart from the methods analyses, we have investigated the prerequisite necessities and final expectations of the NILM system in order to realize an effective one. Initial requirements to establish a well-organized NILM have been described using a concrete analysis to address some important issues. Furthermore, we have explored the primary applications of NILM, considering both customer and utility sides to develop an operative NILM structure. From a realistic standpoint, an advanced NILM aspect has been proposed and its properties have been discussed as the result of a clear understanding of effective NILM requirements and purposes. This concept can lead to a building with integrated system designs and operations. A successful realization of such a concept eventually makes HEMS feasible. Advanced NILM abilities, which can make its actual applications possible, can be considered as the solution for the regressive trend of traditional NILM and create a novel way for the next studies.

– Household database construction approach: In the second analysis, the appliance load modeling issues of capturing the dynamic of power consumption and exhaustive training phases in the NILM context have been tackled. Furthermore, this analysis has intended to notably reduce human intervention in the set-up phases. Consequently, we have proposed the approach of adaptive on-line unsupervised appliance-level load modeling. We have designed a time-variant load modeling procedure for load diagnosis goals of NILM. In fact, the disaggregation methods have been the focal point of NILM studies, which has caused its diagnosis goal to be ignored. Therefore, we have provided a thorough analysis of the essential prerequisites of a NILM system with diagnosis purposes. Our proposed approach has resulted in an autonomous household database construction system. This system utilizes the steady-state operation of household appliances to execute an analysis based on low-sampling frequency, which is compatible with regular smart meters. Furthermore, we have designed an on-line learning system with dynamic HMM parameters. This architecture employs a set of low-complex algorithms to expedite the whole process of appliance database construction. Our database constructor targets the devices with high power consumption whom their accurate energy estimation can assist in a notable cost reduction. The results have demonstrated that our framework is capable of detecting the recurrence of loads' patterns with an accuracy of more than

90% for almost all cases. More importantly, it is able to construct highly accurate (90% and more) models for the majority of appliances with no prior knowledge. Future studies can focus on the improvement of our household database constructor and its utilization for diagnosis systems.

- On-line anomaly detection approach: In the third research, the inadequacy of NILM methods for anomaly detection in the aggregate-level from one side and low-priced smart plugs capabilities from the other side have become the motivation to contribute a practical anomaly detection system in the appliance-level. In fact, anomaly detection accounts for a significant application of load monitoring systems. In the residential sector, anomaly detection can assist with different kinds of energy-saving awareness. Accordingly, we have provided an exhaustive investigation into different perspectives of an appliance-level anomaly detection with regard to household energy-intensive loads. As a result, an on-line load monitoring and anomaly detection approach has been proposed that is capable of expeditiously capturing any operation-time abnormality. The proposed approach has been examined by implementing an actual framework. This framework applies the suggested design to the measured data of a set of appliances candidate. These appliances consist of a standard and a smart refrigerator with different electrical characteristics. Refrigerators are important household finite-state loads that can bring about challenging anomalous behaviors. Therefore, they are a suitable case study for anomaly detection of household energy-expensive loads. The results based on careful diagnostic tests have demonstrated the high performance of our proposed method. In most of the experiments, this method has achieved correctness of more than 95% and around 90% to diagnose the anomaly based on energy and average power consumption, respectively. The high capability of our approach is further validated through its very accurate results in the diagnosis of anomalous events in REFIT database, especially within a long duration analysis (one year). Furthermore, the utilization of a group of straightforward algorithms, examined on a physical operating system has validated the pertinence of the developed structure to smart meters/plugs systems. With regard to the case studies, our analysis has elaborated important remarks on a full appliance-level load monitoring in terms of a system capable of continuous load observation, anomaly detection, and diagnosis decision.

Accordingly, the above conclusion finalizes the extensive analyses, provided in this study to examine the concept of ALMD from different standpoints. Despite all the propositions, the future of this concept highly depends on the manufacture trends in designing a new generation of household appliances based on customer preferences. In fact, the digitalization aspect of future products, capable of independent communication with electricity stakeholders, autonomous decisions, and self-observation can completely change the orientations. Nevertheless, the essence of the proposed approaches, which also concern the desires of customers and system operator should be considered in any future energy estimation and load diagnosis system design that is favored for mass production.

Bibliography

[1] International Energy Agency. *World Energy Outlook 2018: The Future is Electrifying*. 2018.

[2] Hydro-Québec Sustainability report. *Clean energy to power us all*. Tech. rep. 2018.

[3] Damminda Alahakoon and Xinghuo Yu. "Smart Electricity Meter Data Intelligence for Future Energy Systems: A Survey". In: *IEEE Transactions on Industrial Informatics* PP.99 (2015), pp. 1–1. DOI: 10.1109/TII.2015.2414355.

[4] Natural Resources Canada. *Electricity facts*. 2019.

[5] International Energy Agency. *Electricity Statistics*. 2019.

[6] Energy Insights. *Global Energy Perspective 2019 : Reference Case*. 2019.

[7] Global Energy Statistical Yearbook. *Electricity Production Data: World Electricity Statistics*. 2019.

[8] Damminda Alahakoon and Xinghuo Yu. "Smart Electricity Meter Data Intelligence for Future Energy Systems: A Survey". In: *IEEE Transactions on Industrial Informatics* 12.1 (Feb. 2016), pp. 425–436. DOI: 10.1109/TII.2015.2414355.

[9] Sayed Saeed Hosseini, Ali Badri, and Masood Parvania. "A survey on mobile energy storage systems (MESS): Applications, challenges and solutions". In: *Renewable and Sustainable Energy Reviews* 40 (Dec. 2014), pp. 161–170. DOI: 10.1016/j.rser.2014.07.183.

[10] S. Hosseini, S. Kelouwani, K. Agbossou, et al. "A semi-synthetic dataset development tool for household energy consumption analysis". In: *IEEE Int. Conf. Ind. Tech. (ICIT)*. 2017, pp. 564–569. DOI: 10.1109/ICIT.2017.7915420.

[11] Sayed Saeed Hosseini, Kodjo Agbossou, Sousso Kelouwani, et al. "Non-intrusive load monitoring through home energy management systems: A comprehensive review". In: *Renew Sustain Energy Rev* 79.April 2016 (Nov. 2017), pp. 1266–1274. DOI: 10.1016/j.rser.2017.05.096.

[12] Kanghang He, Lina Stankovic, Jing Liao, et al. "Non-Intrusive Load Disaggregation Using Graph Signal Processing". In: *IEEE Transactions on Smart Grid* 9.3 (May 2018), pp. 1739–1747. DOI: 10.1109/TSG.2016.2598872.

[13] Manfred Pöchacker, Dominik Egarter, and Wilfried Elmenreich. "Proficiency of power values for load disaggregation". In: *IEEE Trans. Instrum. Meas.* 65.1 (2016), pp. 46–55. DOI: 10.1109/TIM.2015.2477156.

[14] U.S. Department of Energy. *Advanced Metering Infraestructure and Customer Systems*. Tech. rep. 2016.

[15] N. Calamero, Y. Beck, and D. Shmilovitz. "Defining the unique signatures of loads using the currents' physical components theory and Z-transform". In: *IEEE Transactions on Industrial Informatics* (2015). DOI: 10.1109/TII.2014.2378711.

[16] Pengfei Gao, Shunfu Lin, and Wilsun Xu. "A Novel Current Sensor for Home Energy Use Monitoring". In: *IEEE Transactions on Smart Grid* 5.4 (July 2014), pp. 2021–2028. DOI: 10.1109/TSG.2013.2284760.

[17] Christian Beckel, Wilhelm Kleiminger, Romano Cicchetti, et al. "The ECO data set and the performance of non-intrusive load monitoring algorithms". In: *Proc. 1st ACM Conf. Embedded Syst.* 2014, pp. 80–89. DOI: 10.1145/2674061.2674064.

[18] Giovanni Brusco, Alessandro Burgio, Daniele Menniti, et al. "Energy management system for an energy district with demand response availability". In: *IEEE Transactions on Smart Grid* (2014). DOI: 10.1109/TSG.2014.2318894.

[19] Weicong Kong, Zhao Yang Dong, Jin Ma, et al. "An Extensible Approach for Non-Intrusive Load Disaggregation with Smart Meter Data". In: *IEEE Trans. Smart Grid* 3053.c (2016), pp. 1–1. DOI: 10.1109/TSG.2016.2631238.

[20] L Norford, S Leeb, and D Luo. "Advanced electrical load monitoring: A wealth of information at low cost". In: *Diagnostics for Commercial* (1999), pp. 1–11.

[21] Damien Zufferey, Christophe Gisler, Omar Abou Khaled, et al. "Machine learning approaches for electric appliance classification". In: *2012 11th International Conference on Information Science, Signal Processing and their Applications (ISSPA)*. IEEE, July 2012, pp. 740–745. DOI: 10.1109/ISSPA.2012.6310651.

[22] Maria Noemi Valero Pérez. "A Non-Intrusive Appliance Load Monitoring System for Identifying Kitchen Activities". PhD thesis. Department of Automation and Systems Technology, Aalto University, Espoo, Finland, 2011, pp. 1 –86.

[23] Lei Yang, Xu Chen, Junshan Zhang, et al. "Cost-Effective and Privacy-Preserving Energy Management for Smart Meters". In: *IEEE Transactions on Smart Grid* 6.1 (Jan. 2015), pp. 486–495. DOI: 10.1109/TSG.2014.2343611.

[24] Antonio Ridi, Christophe Gisler, and Jean Hennebert. "Automatic identification of electrical appliances using smart plugs". In: *2013 8th International Workshop on Systems, Signal Processing and their Applications (WoSSPA)*. IEEE, May 2013, pp. 301–305. DOI: 10.1109/WoSSPA.2013.6602380.

[25] Natural Resources Candada. *Energy Fact Book 2019-2020*. Tech. rep. July. 2019.

[26] US Department of Energy. *Estimating Appliance and Home Electronic Energy Use*. 2019.

[27] Dawei He, Weixuan Lin, Nan Liu, et al. "Incorporating non-intrusive load monitoring into building level demand response". In: *IEEE Transactions on Smart Grid* (2013). DOI: 10.1109/TSG.2013.2258180.

[28] Zhijie Xu, Ruisheng Diao, Shuai Lu, et al. "Modeling of Electric Water Heaters for Demand Response: A Baseline PDE Model". In: *IEEE Transactions on Smart Grid* 5.5 (Sept. 2014), pp. 2203–2210. DOI: 10.1109/TSG.2014.2317149.

[29] S. Ali Pourmousavi, Stasha N. Patrick, and M. Hashem Nehrir. "Real-Time Demand Response Through Aggregate Electric Water Heaters for Load Shifting and Balancing Wind Generation". In: *IEEE Transactions on Smart Grid* 5.2 (Mar. 2014), pp. 769–778. DOI: 10.1109/TSG.2013.2290084.

[30] K. Carrie Armel, Abhay Gupta, Gireesh Shrimali, et al. "Is disaggregation the holy grail of energy efficiency? The case of electricity". In: *Energy Policy* 52 (Jan. 2013), pp. 213–234. DOI: 10.1016/j.enpol.2012.08.062.

[31] Sayed Saeed Hosseini, Sousso Kelouwani, Kodjo Agbossou, et al. "Adaptive on-line unsupervised appliance modeling for autonomous household database construction". In: *International Journal of Electrical Power & Energy Systems* 112 (Nov. 2019), pp. 156–168. DOI: 10.1016/j.ijepes.2019.04.034.

[32] Haroon Rashid, Vladimir Stankovic, Lina Stankovic, et al. "Evaluation of Non-intrusive Load Monitoring Algorithms for Appliance-level Anomaly Detection". In: *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. May 2019, pp. 8325–8329. DOI: 10.1109/ICASSP.2019.8683792.

[33] Roberto Bonfigli, Stefano Squartini, Marco Fagiani, et al. "Unsupervised algorithms for non-intrusive load monitoring: An up-to-date overview". In: *2015 IEEE 15th International Conference on Environment and Electrical Engineering (EEEIC)*. IEEE, June 2015, pp. 1175–1180. DOI: 10.1109/EEEIC.2015.7165334.

[34] Yu-Hsiu Lin and Men-Shen Tsai. "An Advanced Home Energy Management System Facilitated by Nonintrusive Load Monitoring With Automated Multiobjective Power Scheduling". In: *IEEE TRANSACTIONS ON SMART GRID* 6.4 (2015). DOI: 10.1109/TSG.2015.2388492.

[35] Oliver Parson. *Disaggregated Homes: Public Data Sets for NIALM*. 2016.

[36] Stephen Makonin, Fred Popowich, Ivan V. Bajic, et al. "Exploiting HMM Sparsity to Perform Online Real-Time Nonintrusive Load Monitoring". In: *IEEE Transactions on Smart Grid* 7.6 (Nov. 2016), pp. 2575–2585. DOI: 10.1109/TSG.2015.2494592.

[37] Sean Barker, Sandeep Kalra, David Irwin, et al. "Empirical characterization, modeling, and analysis of smart meter data". In: *IEEE Journal on Selected Areas in Communications* 32.7 (2014), pp. 1312–1327. DOI: 10.1109/JSAC.2014.2332107.

[38] Kien Nguyen Trung, Eric Dekneuvel, Benjamin Nicolle, et al. "Using FPGA for real time power monitoring in a NIALM system". In: *IEEE International Symposium on Industrial Electronics* (2013), pp. 3–8. DOI: 10.1109/ISIE.2013.6563850.

[39] Michael Zeifman and Kurt Roth. "Nonintrusive Appliance Load Monitoring: Review and Outlook". In: *IEEE Transactions on Consumer Electronics* 57.1 (2011).

[40] Ahmed Zoha, Alexander Gluhak, Muhammad Imran, et al. "Non-Intrusive Load Monitoring Approaches for Disaggregated Energy Sensing: A Survey". In: *Sensors* 12.12 (2012), pp. 16838–16866. DOI: 10.3390/s121216838.

[41] Dominik Egarter, Venkata Pathuri Bhuvana, and Wilfried Elmenreich. "PALDi: Online load disaggregation via particle filtering". In: *IEEE Transactions on Instrumentation and Measurement* (2015). DOI: 10.1109/TIM.2014.2344373.

[42] S. Hosseini, N. Henao, S. Kelouwani, et al. "A Study on Markovian and Deep Learning Based Architectures for Household Appliance-level Load Modeling and Recognition". In: *IEEE 28th International Symposium on Industrial Electronics (ISIE)* (2019), pp. 35–40. DOI: 10.1109/isie.2019.8781186.

[43] Dominik Egarter, Venkata Pathuri Bhuvana, and Wilfried Elmenreich. "PALDi: Online load disaggregation via particle filtering". In: *IEEE Trans. Instrum. Meas.* (2015). DOI: 10.1109/TIM.2014.2344373.

[44] Oliver Parson, Siddhartha Ghosh, Mark Weal, et al. "An unsupervised training method for non-intrusive appliance load monitoring". In: *Artificial Intelligence* 217 (Dec. 2014), pp. 1–19. DOI: 10.1016/j.artint.2014.07.010.

[45] Kien Nguyen Trung, Olivier Zammit, Eric Dekneuvel, et al. "An innovative non-intrusive load monitoring system for commercial and industrial application". In: *The 2012 International Conference on Advanced Technologies for Communications*. Atc. IEEE, Oct. 2012, pp. 23–27. DOI: 10.1109/ATC.2012.6404221.

[46] Stephen Makonin. "Investigating the switch continuity principle assumed in Non-Intrusive Load Monitoring (NILM)". In: *2016 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)*. Ccece. IEEE, May 2016, pp. 1–4. DOI: 10.1109/CCECE.2016.7726787.

[47] Po-an Chou and Ray-i Chang. "Unsupervised Adaptive Non-intrusive Load Monitoring System". In: *2013 IEEE International Conference on Systems, Man, and Cybernetics*. IEEE, Oct. 2013, pp. 3180–3185. DOI: 10.1109/SMC.2013.542.

[48] Tuomo Alasalmi, Jaakko Suutala, and J Röning. "REAL-TIME NON-INTRUSIVE APPLIANCE LOAD MONITOR - Feedback System for Single-point per Appliance Electricity Usage". In: *Proceedings of the 1st International Conference on Smart Grids and Green IT Systems*. SciTePress - Science, and Technology Publications, 2012, pp. 203–208. DOI: 10.5220/0003951802030208.

[49] Bochao Zhao, Lina Stankovic, and Vladimir Stankovic. "On a Training-Less Solution for Non-Intrusive Appliance Load Monitoring Using Graph Signal Processing". In: *IEEE Access* 4 (2016), pp. 1784–1799. DOI: 10.1109/ACCESS.2016.2557460.

[50] Franz Rammig, Michael Ditze, Peter Janacik, et al. "Basic Concepts of Real Time Operating Systems". In: *Hardware-dependent Software*. Dordrecht: Springer Netherlands, 2009, pp. 15–45. DOI: 10.1007/978-1-4020-9436-1{_}2.

[51] M Baker, G Hicks, S Rodriguez, et al. "A Test of Commercially Available Products for Estimating End Uses from Smart Meter Data". In: *NILM workshop 2016*. 2016.

[52] Varun Chandola, Arindam Banerjee, and Vipin Kumar. "Anomaly detection". In: *ACM Computing Surveys* 41.3 (July 2009), pp. 1–58. DOI: 10.1145/1541880.1541882.

[53] Lorenzo Fernandez Maimo, Angel Luis Perales Gomez, Felix J. Garcia Clemente, et al. "A Self-Adaptive Deep Learning-Based System for Anomaly Detection in 5G Networks". In: *IEEE Access* 6 (2018), pp. 7700–7712. DOI: 10.1109/ACCESS.2018.2803446.

[54] Evan Mills. "Building commissioning: a golden opportunity for reducing energy costs and greenhouse gas emissions in the United States". In: *Energy Efficiency* 4.2 (May 2011), pp. 145–173. DOI: 10.1007/s12053-011-9116-8.

[55] Q. Yang. "Model-Based and Data Driven Fault Diagnosis Methods with Applications to Process Monitoring". PhD thesis. Case Western Reserve University, 2004.

[56] Sayed Saeed Hosseini, Kodjo Agbossou, Sousso Kelouwani, et al. "Non-intrusive load monitoring through home energy management systems: A comprehensive review". In: *Renewable and Sustainable Energy Reviews* 79 (Nov. 2017), pp. 1266–1274. DOI: 10.1016/j.rser.2017.05.096.

[57] Haroon Rashid, Pushpendra Singh, Vladimir Stankovic, et al. "Can non-intrusive load monitoring be used for identifying an appliance's anomalous behaviour?" In: *Applied Energy* 238 (2019), pp. 796–805. DOI: 10.1016/j.apenergy.2019.01.061.

[58] Shaopeng Zhai, Zhihua Wang, Xufeng Yan, et al. "Appliance Flexibility Analysis Considering User Behavior in Home Energy Management System Using Smart Plugs". In: *IEEE Transactions on Industrial Electronics* 66.2 (Feb. 2019), pp. 1391–1401. DOI: 10.1109/TIE.2018.2815949.

[59] S.R. Shaw, S.B. Leeb, L.K. Norford, et al. "Nonintrusive Load Monitoring and Diagnostics in Power Systems". In: *IEEE Transactions on Instrumentation and Measurement* 57.7 (July 2008), pp. 1445–1454. DOI: 10.1109/TIM.2008.917179.

[60] G.W. Hart. "Nonintrusive appliance load monitoring". In: *Proc. IEEE* 80.12 (1992), pp. 1870–1891. DOI: 10.1109/5.192069.

[61] Michael Zeifman and Kurt Roth. "Viterbi algorithm with sparse transitions (VAST) for nonintrusive load monitoring". In: *IEEE Symp. Compon. Intell. Appl. Smart Grid (CIASG)*. IEEE, 2011, pp. 1–8. DOI: 10.1109/CIASG.2011.5953328.

[62] J Zico Kolter and Matthew J Johnson. "REDD : A Public Data Set for Energy Disaggregation Research". In: *SustKDD workshop* 1 (2011), pp. 1–6.

[63] Kaustav Basu, Vincent Debusschere, Seddik Bacha, et al. "Nonintrusive Load Monitoring: A Temporal Multilabel Classification Approach". In: *IEEE Transactions on Industrial Informatics* 11.1 (Feb. 2015), pp. 262–270. DOI: 10.1109/TII.2014.2361288.

[64] Zhenyu Guo, Z Jane Wang, and Ali Kashani. "Home Appliance Load Modeling From Aggregated Smart Meter Data". In: *IEEE Trans. Power Syst.* 30.1 (2015). DOI: 10.1109/TPWRS.2014.2327041.

[65] Hannu Pihala. "Non-intrusive appliance load monitoring system based on a modern kWh-meter". In: *VTT Publications* 356 (1998), p. 68.

[66] Michael Zeifman and Kurt Roth. "Nonintrusive appliance load monitoring: Review and outlook". In: *IEEE Transactions on Consumer Electronics* 57.1 (Feb. 2011), pp. 76–84. DOI: 10.1109/TCE.2011.5735484.

[67] Yu Hsiu Lin and Men Shen Tsai. "Non-intrusive load monitoring by novel neuro-fuzzy classification considering uncertainties". In: *IEEE Transactions on Smart Grid* (2014). DOI: 10.1109/TSG.2014.2314738.

[68] Martin Šíra and Věra Nováková Zachovalová. "System for Calibration of Nonintrusive Load Meters With Load Identification Ability". In: *IEEE Transactions on Instrumentation and Measurement* 64.6 (2015), pp. 1350–1354. DOI: 10.1109/TIM.2015.2399021.

[69] Steven B. Leeb, Steven R. Shaw, and James L. Kirtley. "Transient event detection in spectral envelope estimates for nonintrusive load monitoring". In: *IEEE Transactions on Power Delivery* 10.3 (1995), pp. 1200–1210. DOI: 10.1109/61.400897.

[70] Wilsun Xu, Pengfei Gao, and Shunfu Lin. "A novel current sensor for home energy use monitoring". In: *2014 IEEE PES General Meeting | Conference & Exposition*. Vol. 5. 4. IEEE, July 2014, pp. 1–1. DOI: 10.1109/PESGM.2014.6938999.

[71] Youn-Kyu Seo and Won-Hwa Hong. "Constructing electricity load profile and formulating load pattern for urban apartment in Korea". In: *Energy and Buildings* 78 (Aug. 2014), pp. 222–230. DOI: 10.1016/j.enbuild.2014.03.007.

[72] Warit Wichakool, Zachary Remscrim, Uzoma A. Orji, et al. "Smart metering of variable power loads". In: *IEEE Transactions on Smart Grid* (2015). DOI: 10.1109/TSG.2014.2352648.

[73] Yu-Hsiu Lin and Men-Shen Tsai. "Development of an Improved Time–Frequency Analysis-Based Nonintrusive Load Monitor for Load Demand Identification". In: *IEEE Trans. Instrum. Meas.* 63.6 (June 2014), pp. 1470–1483. DOI: 10.1109/TIM.2013.2289700.

[74] Seyed Mostafa Tabatabaei, Scott Dick, and Wilsun Xu. "Towards Non-Intrusive Load Monitoring via Multi-Label Classification". In: *IEEE Transactions on Smart Grid* 3053.c (2016), pp. 1–1. DOI: 10.1109/TSG.2016.2584581.

[75] Zico Kolter and Tommi Jaakkola. "Approximate Inference in Additive Factorial HMMs with Application to Energy Disaggregation". In: *Proc. Int. Conf. Arti. Intell. Statist.* (2012), pp. 1472–1482.

[76] N. Henao. "Désagrégation Non-Intrusive de Charges Électriques Résidentielles Septembre". PhD thesis. University of Quebec at Trois-Rivieres, 2018.

[77] Marisa Figueiredo, Ana de Almeida, and Bernardete Ribeiro. "Home electrical signal disaggregation for non-intrusive load monitoring (NILM) systems". In: *Neurocomputing* 96 (Nov. 2012), pp. 66–73. DOI: 10.1016/J.NEUCOM.2011.10.037.

[78] Hsueh-hsien Chang, Po-ching Chien, Lung-shu Lin, et al. "Feature Extraction of Non-intrusive Load-Monitoring System Using Genetic Algorithm in Smart Meters". In: *2011 IEEE 8th International Conference on e-Business Engineering*. IEEE, Oct. 2011, pp. 299–304. DOI: 10.1109/ICEBE.2011.48.

[79] Men-Shen Tsai and Yu-Hsiu Lin. "Modern development of an Adaptive Non-Intrusive Appliance Load Monitoring system in electricity energy conservation". In: *Applied Energy* 96 (Aug. 2012), pp. 55–73. DOI: 10.1016/j.apenergy.2011.11.027.

[80] Mario E. Berges, Ethan Goldman, H. Scott Matthews, et al. "Enhancing Electricity Audits in Residential Buildings with Nonintrusive Load Monitoring". In: *Journal*

of Industrial Ecology 14.5 (Oct. 2010), pp. 844–858. DOI: 10.1111/j.1530-9290.2010.00280.x.

[81] Krishnan Srinivasarengan, Y.G. Goutam, M Girish Chandra, et al. "A Framework for Non Intrusive Load Monitoring Using Bayesian Inference". In: *2013 Seventh International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing*. IEEE, July 2013, pp. 427–432. DOI: 10.1109/IMIS.2013.78.

[82] Karim Said Barsim and Bin Yang. "Toward a semi-supervised non-intrusive load monitoring system for event-based energy disaggregation". In: *2015 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*. IEEE, Dec. 2015, pp. 58–62. DOI: 10.1109/GlobalSIP.2015.7418156.

[83] Sundeep Pattem. "Unsupervised Disaggregation for Non-intrusive Load Monitoring". In: *2012 11th International Conference on Machine Learning and Applications*. IEEE, Dec. 2012, pp. 515–520. DOI: 10.1109/ICMLA.2012.249.

[84] Dominik Egarter and Wilfried Elmenreich. "Autonomous load disaggregation approach based on active power measurements". In: *2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops)*. IEEE, Mar. 2015, pp. 293–298. DOI: 10.1109/PERCOMW.2015.7134051.

[85] Jing Liao, Georgia Elafoudi, Lina Stankovic, et al. "Power Disaggregation for Low-sampling Rate Data". In: *2nd Int. Non-intrusive Appliance Load Monitoring Workshop*. 2014.

[86] Jessie M Gillis, Sami M Alshareef, and Walid G Morsi. "Nonintrusive Load Monitoring Using Wavelet Design and Machine Learning". In: *IEEE Transactions on Smart Grid* 7.1 (Jan. 2016), pp. 320–328. DOI: 10.1109/TSG.2015.2428706.

[87] Nilson Henao, Kodjo Agbossou, Sousso Kelouwani, et al. "Approach in Nonintrusive Type I Load Monitoring Using Subtractive Clustering". In: *IEEE Trans. Smart Grid* 8.2 (2015), pp. 812–821. DOI: 10.1109/TSG.2015.2462719.

[88] Hyungsul Kim, Manish Marwah, Martin Arlitt, et al. “Unsupervised Disaggregation of Low Frequency Power Measurements”. In: *Proceedings of the 2011 SIAM International Conference on Data Mining*. 2011, pp. 747–758. DOI: 10.1137/1.9781611972818.64.

[89] Pierre Ferrez and Pierre Roduit. “Non-intrusive appliance load curve disaggregation for service development”. In: *ENERGYCON 2014 - IEEE International Energy Conference* (2014), pp. 813–820. DOI: 10.1109/ENERGYCON.2014.6850519.

[90] Irfan Ullah, Fan Yang, Rehanullah Khan, et al. “Predictive Maintenance of Power Substation Equipment by Infrared Thermography Using a Machine-Learning Approach”. In: *Energies* 10.12 (Dec. 2017), p. 1987. DOI: 10.3390/en10121987.

[91] Shizhen Chang, Bo Du, and Liangpei Zhang. “BASO: A Background-Anomaly Component Projection and Separation Optimized Filter for Anomaly Detection in Hyperspectral Images”. In: *IEEE Transactions on Geoscience and Remote Sensing* 56.7 (July 2018), pp. 3747–3761. DOI: 10.1109/TGRS.2018.2810124.

[92] Kun Xie, Xiaocan Li, Xin Wang, et al. “Fast Tensor Factorization for Accurate Internet Anomaly Detection”. In: *IEEE/ACM Transactions on Networking* 25.6 (Dec. 2017), pp. 3794–3807. DOI: 10.1109/TNET.2017.2761704.

[93] Manas Khatua, Seyed Hamid Safavi, and Ngai Man Cheung. “Detection of Internet Traffic Anomalies Using Sparse Laplacian Component Analysis”. In: *in Proc. of IEEE Global Communications Conference, GLOBECOM* (2018), pp. 1–6. DOI: 10.1109/GLOCOM.2017.8254833.

[94] Nur Ashar Aditiya, Muhammad Rizky Dharmawan, Zaqiatud Darojah, et al. “Fault diagnosis system of rotating machines using Hidden Markov Model (HMM)”. In: *IEEE International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC)*. 2017, pp. 177–181. DOI: 10.1109/KCIC.2017.8228583.

[95] Tushar, Shikhar Pandey, Anurag K. Srivastava, et al. “Online Estimation of Steady-State Load Models Considering Data Anomalies”. In: *IEEE Transactions on Industry Applications* 54.1 (2018), pp. 712–721. DOI: 10.1109/TIA.2017.2753719.

[96] Songyan Wang, Shixiong Fan, Jianwen Chen, et al. “Deep-learning based fault diagnosis using computer-visualised power flow”. In: *IET Generation, Transmission & Distribution* 12.17 (Sept. 2018), pp. 3985–3992. DOI: 10.1049/iet-gtd.2018.5254.

[97] Junho Hong, Chen-Ching Liu, and Manimaran Govindarasu. “Integrated Anomaly Detection for Cyber Security of the Substations”. In: *IEEE Transactions on Smart Grid* 5.4 (July 2014), pp. 1643–1653. DOI: 10.1109/TSG.2013.2294473.

[98] Wenqiang Cui and Hao Wang. “Anomaly detection and visualization of school electricity consumption data”. In: *IEEE 2nd International Conference on Big Data Analysis (ICBDA)*. 2017, pp. 606–611. DOI: 10.1109/ICBDA.2017.8078707.

[99] Yunxian Jia, Lei Sun, and Hongzhi Teng. “A comparison study of hidden Markov model and particle filtering method: Application to fault diagnosis for gearbox”. In: *Proc. of the IEEE Prognostics and System Health Management Conference (PHM-2012 Beijing)*. May 2012, pp. 1–7. DOI: 10.1109/PHM.2012.6228865.

[100] Ramon Granell, Colin J. Axon, and David C H Wallom. “Impacts of Raw Data Temporal Resolution Using Selected Clustering Methods on Residential Electricity Load Profiles”. In: *IEEE Transactions on Power Systems* 30.6 (Nov. 2015), pp. 3217–3224. DOI: 10.1109/TPWRS.2014.2377213.

[101] Zuyuan Yang, Yong Xiang, Kan Xie, et al. “Adaptive Method for Nonsmooth Nonnegative Matrix Factorization”. In: *IEEE Transactions on Neural Networks and Learning Systems* 28.4 (Apr. 2017), pp. 948–960. DOI: 10.1109/TNNLS.2016.2517096.

[102] Yun-Qian Miao. “Adaptive Learning Algorithms for Non-stationary Data”. PhD thesis. University of Waterloo, 2015.

Appendix A - Electrically similar appliances identification

A Study on Markovian and Deep Learning Based Architectures for Household Appliance-level Load Modeling and Recognition

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***Abstract*—The promise of non-intrusive approach of Appliance Load Monitoring (ALM) promotes the load decomposition analysis at the most disaggregated level. Accordingly, appliance-level load modeling is bolstered to provide appliance-level information and quantify energy consumption. This paper intends to investigate the proficiency of Markovian models, as the state-of-the-art and Deep Learning (DL) architectures, as the cutting-edge of machine learning methods for load modeling through disaggregation practice. Particularly, a simple Recurrent Neural Network (RNN) as a fundamental network architecture for DL is chosen, which is consistent with first-order Markovian chain assumption. A dataset with a challenging load disaggregation case is utilized for the analysis. The same learning mechanism is used to execute the training phase of both approaches, regarding a fair performance comparison. Consequently, the recognition accuracy of the algorithms is evaluated. The results demonstrate that Markov decision procedure is comparable with DL basic manner. Additionally, the paper elaborates remarks on essential prerequisites, specifically data adequacy, to provide a thorough load modeling analysis. From a practical standpoint, this work aims to pinpoint major barriers in terms of both load model construction and recognition towards actual implementation.**

***Index Terms*—Markov models, Deep learning, Recurrent neural networks, Load modeling, Disaggregation.**

I. Introduction

Household appliances load monitoring at the most disaggregated level is signified due to energy saving potential awareness [1]. Accordingly, the approach of appliance-level load modeling, widely practiced in the context of Non-Intrusive Load Monitoring (NILM), is promoted to provide appliance-level information, [2]. Correspondingly, different techniques have been exploited to meet load modeling, among which, probabilistic approaches specifically, Hidden Markov Models (HMM) have received a significant attention. HMM methods are capable of providing analytical state-based models of household appliances by enabling sequential data analysis [3], [4]. In fact, the variants of HMM are the state-of-the-art approaches especially, in low-sampling rate analyses of household total signal [5]. Recently, the promise of Deep Neural Networks (DNN) have provided a meaningful success in data processing in many areas as images, texts, and audios [6]. Therefore, they have been taken into consideration for load modeling as the cutting-edge research [7].

Consequently, a comparative study between DNN and superior variants of HMM can be advantageous for further studies in the early stages. In fact, this comparison is sensible due to the fact that they are both generative approaches, which their analytical techniques demonstrate a Bayesian nature [6]. This paper aims to provide a comparison between HMM and DNN methods, employed in appliance-level load modeling under the same conditions. Indeed, the tendency of few similar studies signifies the application of DL architectures. Kim *et al.* [8] discusses the difficulty of FHMM in recognition of appliances with the same power consumption, where the total power demand is the only observation. However, appliances identification with identical demands in such situation is a fundamental NILM issue that can also matter DNN methods. Marques [6] expresses the ability of DNN means to achieve valuable results with almost no prior information. Nonetheless, due to a large parameter space, DL algorithms require a great amount of prior knowledge to provide effective models [6], [9]. Indeed, the availability of large amount of data is a significant reason of recent DNN achievements.

Accordingly, in order to provide a careful analysis, this paper first discusses the dataset candidate proficiency due to its influence over the accuracy of the methods. Furthermore, a simple Recurrent Neural Network (RNN) with short-term memory as a fundamental DL architecture is chosen due to its consistency with first-order Markovian chain assumption [10]. On the other side, two variants of HMM are studied, which consist of Factorial HMM (FHMM) and Hidden Semi-Markov Models (HSMM), also known as Explicit Duration HMM (EDHMM). In fact, FHMM is capable of explaining the additive effect of aggregated signal, and HSMM is capable of modeling the operation time of individual loads. Therefore, they can enable a practical modeling framework regarding real-world behavior of household appliances [10], [11]. Moreover, a supervised machine learning process that utilizes straightforward training techniques to construct appliance-level models, is exploited for both methods. Consequently, the load disaggregation technique is used to evaluate the performance of the approaches in providing an accurate inference of load operation states. In fact, this work demonstrates that the superior variants of HMM are competitive with DNN models under the same conditions. In addition, the paper provides sensible remarks by detailing the manner of both approaches to model and recognize household appliance-level loads.

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The rest of the paper is organized as follows. Section II presents appliance-level load modeling formulation based on the suggested methods. Section III describes the case study and discusses important notes regarding the essentials of the exploited algorithms. Section IV provides the results with related discussion, followed by the conclusion remarks in Section V.

II. Problem Modeling and Specification

Our methodology for investigating opportunities and challenges regarding household appliance-level load modeling by using HMM and RNN is developed through the followings.

A. RNN Framework

A deep learning structure is developed based on a simple Recurrent Neural Network (RNN) as a basic model of DNN, designed to recognize patterns in data sequence [12]. The simple RNN decision at time instant t depends not only on the current input but also the net state at time $t-1$. This configuration provides a feedback loop directly connected to the past decisions and permit a temporal behavior. In fact, such RNN facilitates correlation investigation between time-separated events as short-term dependencies by allowing the information circulation in the hidden layers. Accordingly, the network creates a memory that enables sequential analysis to capture the information of data sequence, essential for household load modeling and impossible with feed-forward networks [13]. The utilized net structure, proposed by Elman and known as Vanilla RNN [14], is shown in Fig. 1. In this structure, the update rule of forward path parameters is defined by (1).

$$\begin{aligned} h_t &= \sigma\left(W_Y Y_t + W_h h_{t-1}\right) \\ S_t &= \theta\left(W_S h_t\right) \end{aligned} \tag{1}$$

where at time step t, Y_t is the input i.e. observations, h_t defines the context (hidden) state, and S_t presents the output i.e. load operation states. W_Y and W_S are the input and output weight matrices, respectively. W_h characterizes the hidden weight matrix as a transition matrix that is comparable to Markov chain. σ and θ express the activation functions of context and output layers, respectively.

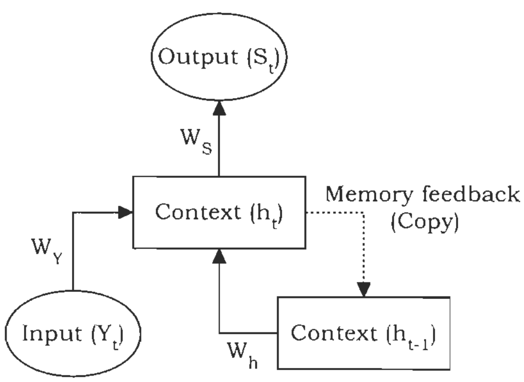


Fig. 1. The diagram of the simple RNN structure known as Vanilla RNN.

The RNN is trained using backpropagation of error and gradient-based optimization methods as feed-forward nets. However, the essence of RNN relies on an algorithm that applies time to the series of training calculations in order to link the time steps, called Backpropagation through time (BPTT).

B. FHMM structure

FHMM can be described as a generalization of HMM, proposed by Ghahramani and Jordan [15] in terms of a dynamic network of composed underlying Markov chains as shown in Fig. 2. The FHMM hidden state is defined as a collection of states of individual HMM with independent dynamics, [10] expressed by (2).

$$S_t = S_t^{(1)}, ..., S_t^{(m)}, ..., S_t^{(M)} \tag{2}$$

In fact, each network layer as a HMM is characterized by its state space $Q^{(m)}$ and emission distribution $Y_t^{(m)}$ that at time t, determine its state variable and describes the observation sequence through (3).

$$\hat{Y}_t = f\left(Y_t^{(1)}, ..., Y_t^{(m)}, ..., Y_t^{(M)}\right) \tag{3}$$

A simplified FHMM consists of individual HMM with both equal number of state variables and constrained transitions between states in different layers. Accordingly, the dynamic of such structure can be captured through analyzing the evolution of each HMM state variables separately, defined by (4).

$$S_t \mid S_{t-1} \sim \prod_{m=1}^{M} P\left(S_t^{(m)} \mid S_{t-1}^{(m)}\right) \tag{4}$$

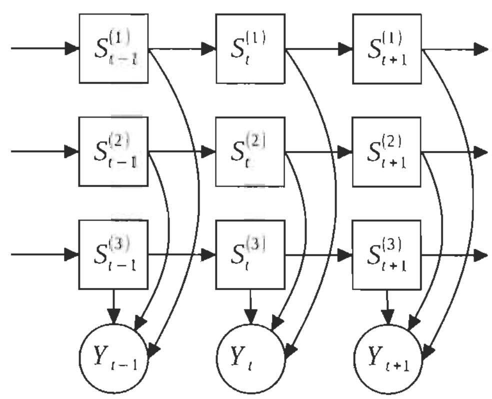


Fig. 2. The diagram of the FHMM structure with discrete hidden states.

Appliance-level load modeling based on active power consumption, as the focus of this study relies on household total load in terms of the observation. In this case, a derivation, referred to as an additive FHMM is generally employed in which the observation is the sum of appliance emissions, explained by (5),

$$\hat{Y}_t = \sum_{m=1}^{M} Y_t^{(m)} \tag{5}$$

that every individual appliance emission is assumed to follow a Normal distribution at each operation state, computed by (6).

$$Y_t^{(m)} \mid q_{(1:K)}^{(m)} \sim \mathcal{N}\left(\mu_{(1:K)}^{m}, \sigma_{(1:K)}^{m}\right) \tag{6}$$

Due to the time complexity, the additive model faces difficulties to provide an exact inference estimation by using dynamic programming procedures, utilized by traditional HMM. Therefore, approximative inference procedures such as Markov Chain Monte Carlo (MCMC) methods and reduced forward-backward algorithms are exploited to interpret the most probable state sequence [10].

In addition, the learning phase of a FHMM can be done through parameter estimation of the model structure by employing Expectation Maximization (EM) algorithm. However, due to the expensive computation of the posterior probabilities, other efficient algorithms are signified [15].

C. HSMM structure

The idea of HSMM allows to model the sojourn time of a Markov process as the duration that an HMM lies in a state [11]. The HSMM is promoted due to the fact that the inherent state duration of an HMM follows a geometrical distribution that is inadequate to model the real-world behavior of appliances' operation. HSMM design, shown in Fig. 3, enables both the estimation of state duration distributions d_t regarding the associated occurring observations as well as the effective inference of the underlying state sequence [16].

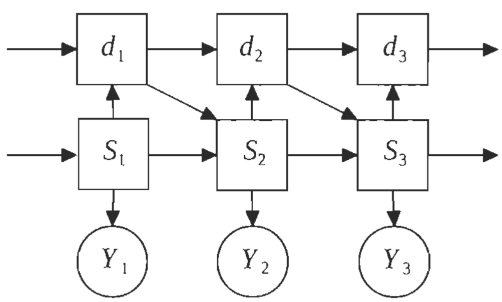


Fig. 3. The diagram of the HSMM structure denoted as EDHMM.

A HSMM preserves the Markov property, i.e. $p(S_t = q_j \mid S_1 ... S_{t-1}) = p(S_t = q_j \mid S_{t-1} = q_i)$ that $1 \leqslant i, j \leqslant K$ for K number of states and each latent state is infused with its duration distribution, $p(d_t \mid S_t = q_j)$. Accordingly, the state duration, drawn from its own distribution in a specific time instant constrains the transitions from that state. Principally, a decrement counter is utilized to count down d_t and allows the current state to change when it is zero, explained by (7).

$$p(S_t = q_j \mid S_{t-1} = q_i, d_{t-1}) = \begin{cases} \delta(i, j), & d > 0\,(\text{remain}) \\ a_{ij}, & d = 0\,(\text{transition}) \end{cases} \tag{7}$$

Where the delta function, $\delta(i, j)$ and transition matrix elements, $A = \{a_{ij}\}$ perform the determined actions. Subsequently, the zero counter is reset to the duration of the next state, described by (8) [16].

$$p(d_t \mid S_t = q_j, d_{t-1}) = \begin{cases} \delta(d_t, d_{t-1} - 1) \text{ if } d_{t-1} > 1 \\ p(d_t \mid S_t = q_j) \text{ otherwise} \end{cases} \tag{8}$$

As a result, the join probability distribution of a particular observation sequence in a HSMM structure can be computed through (9).

$$p(Y, S, D) = \prod_{t=1}^{T} p(y_t \mid S_t, d_t) \times \prod_{t=1}^{T} p(S_t \mid S_{t-1}, d_{t-1}) \times \prod_{t=1}^{T} p(d_t \mid S_t, d_{t-1}) \tag{9}$$

The contribution of the state duration probability in the forward algorithm can be realized in the equation (9). The parameter estimation and inference of a HSMM structure can be theoretically done using conventional methods applied for regular HMM. However, these methods can be complex. Accordingly, MCMC techniques such as Gibbs sampling can be utilized to provide an efficient procedure [16]. Moreover, these techniques can take advantage of forward-backward algorithms to offer a superior posterior estimation [11].

III. Case Study Implementation and Discussion

The problem structure is developed by defining the essential prerequisite to provide an actual viewpoint of the performance of the utilized methods. This consists of an appropriate dataset candidate of household appliances and initialization of the algorithms particularly, RNN. It is noted that our problem is coded using Python language that provides convenient libraries for HMM and DL experimentation. The load modeling analysis is done by using the steady-state feature of power consumption data in a low-sampling rate of one minute. Indeed, lower-sampling frequencies are compatible with world-wide tendency of smart meter technologies in data transfer however, they can hinder the load disaggregation task [17].

A. Dataset Candidate

We utilize the real-data of ECO (Electricity Consumption and Occupancy) dataset, qualified for load disaggregation studies [18]. The proficiency of ECO data in comparison with other datasets has been demonstrated in [1]. Particularly, aggregated data of ECO house 2 is used as a challenging case for load disaggregation due to high overlapping rates (simultaneous operations) and existing loads with similar power demands [19]. The targeted household appliances are comprised of fridge, freezer, dishwasher, kettle, and HTPC (Home Theater PC). The simultaneous presence of fridge and freezer in this case brings about difficult recognition tasks due to similarity in the power consumption and operation behaviors. Indeed, the combination of common periodic devices with similar power demands can demonstrate the difficulty of identical loads disaggregation as a common complication faced by load modeling methods. However, this issues is generally lacked in other studies, utilized REDD (Reference Energy

Disaggregation Dataset) as another widely exploited dataset [20], [21].

The importance of an efficient acquisition system as dataset builder increases with DL methods specifically, in the training phase [1]. Basically, the rate of missing data, especially gaps can significantly jeopardize the training procedure through changing the spaced samples length fed to DNN batches. Consequently, such practice causes DNN to learn varying patterns at each time window [6]. As a result, a data preprocessing step is a prerequisite of load modeling analyses that utilize DL methods. Likewise, Markov-based analyses require the preprocessing phase. However, in this regard, they do not face crucial challenges and thus; detailing this phase has been skipped in the related studies.

From a technical viewpoint, household appliances consist of periodic e.g. fridge, regular e.g. water heater, and irregular e.g. vacuum cleaner loads with different operation schedules. Accordingly, a large amount of data is essential for a successful training however, available data is limited with regard to household appliances' load space [22], [23]. Particularly, the size of data influences DNN learning phase due to the huge number of parameters. In fact, the collected data should be long enough to account for different combinations of appliances' operation to build a deep model structure [6]. Nevertheless, the available data still requires a computationally powerful system since, DNN can pass through many multiplication steps. In this regard, it should be mentioned that another issue with REDD is a short duration measurement of 3 to 19 days with long gaps of missing information [1].

B. RNN designation

The RNN structure is designed using Keras as an open-source Python-DL library of high-level neural networks. Keras is a user-friendly and easy-extensible framework to enable easy and fast practices regarding conventional and recurrent networks [24]. Accordingly, a Sequential model of Keras core-data structure is chosen. Consequently, a fully connected RNN that consists of two hidden layers of 14 units in each, and an out-put layer consistent with the number of load models, is developed. In addition, Rectified Linear Unit (relu) and Sigmoid functions are considered as the activation functions in context and output layers, respectively. Subsequently, the network is compiled using Adam, as the optimization algorithm and mean squared error as the loss function. In fact, different structures and optimizer have been tried, among which the above structure with Adam (a stochastic gradient-based optimizer) has surpassed the other choices for our case. The effectiveness of the configurations is evaluated by network fitting process within training on the dataset. As a result, the RNN is trained over a sliding window of 7 inputs, indexed in time to form a time-series. The training phase is advanced within 20 epochs, partitioned into groups of 60 batches to avoid loading too many inputs into the network memory at once. Due to the wide range of power data values, the inputs are standardized between $[0, 1]$ for an effective training [6]. Fig. 4 depicts the training platform of the RNN. Indeed,

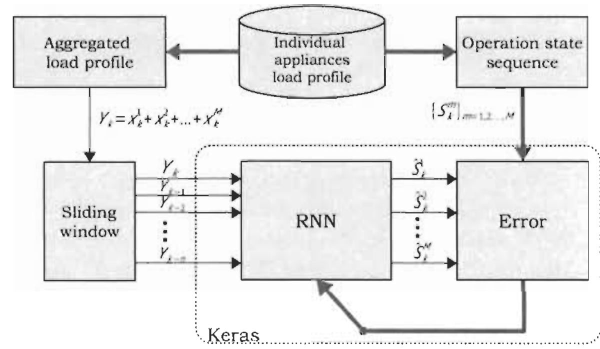


Fig. 4. The block diagram of the RNN training structure.

the designation of DNN architecture deals with important adjustments, which may not be the case of HMM as their fundamentals signify sequential analysis applicable for time-series exploration.

C. FHMM and HSMM designation

The Markov models are not confronted with manners that DNN models undergo for network design and fit specifically, in the context of a supervised learning. In fact, the HMM is a practical approach for exploratory data analysis of time series. Especially, using the underlying models, it can effectively describe the aggregate effect of total signal through factorial models. Accordingly, the main step is to define the structure of the HMM that automatically describes the set of parameters to estimate. Considering the targeted loads, a two-state HMM is chosen that its parameters are obtained from individual load profiles. The Baum-Welch algorithm can be used for parameter estimation however, there are simpler methods for two-state load profiles. In this case, the state probabilities are computed by defining the on/off operation states using a threshold. Consequently, the related emission parameters of each state is calculated as a Normal distribution according to (6). As a result, the HMM parameter set of each targeted load, consisting of initial and transition probabilities as well as state-sequence time and emission distributions are constructed.

In fact, the training phase of Markov-based methods using individual load profiles facilitates learning procedure with less amount of required data. However, the RNN training manner needs to capture the combination of individual profiles that becomes critical with the increase in the number of loads with limited data. Nevertheless, both approaches are sensitive to the presence of unknown loads that decline their efficiency.

IV. Result and Evaluation

Our results is a consequence of concerning both the proficiency of the data and the adequacy of the methods crucial to a fruitful appliance-level modeling process. The training phase of the utilized methods is executed using the targeted loads' data of fifteen days, started at 10th day (based on ECO house 2 information). Subsequently, the evaluation phase is practiced using another 15 days of unseen data, started from 30th day. In fact, the efficiency of the model parameters of the chosen loads, captured through the training phase is examined in the context of a disaggregation procedure. The RNN interpretation is met by the evaluation of the loss function on the new data. Furthermore, FHMM inference is realized using the Gibbs sampling method, exploited in [10]. Nonetheless, in a space with less number of models, the factorial model can be determined to allow unrestricted transitions to create a regular super-state HMM. Subsequently, such HMM can be decoded using Viterbi algorithm to provide the state sequence inference of load models. Additionally, the HSMM is extended into a Factorial model as FHSMM that is evaluated using the same inference procedure as FHMM. Moreover, the f_1-score, as a widely used metric for single-label classification is employed to explore the methods' accuracy performance [7], expressed by (10)

$$f_1 = \frac{2 \times precision \times recall}{precision + recall} \tag{10}$$

that $precision = \frac{t_p}{t_p + f_P}$ and $recall = \frac{t_p}{t_p + f_n}$, in which t_p is true positives, which is the number of times an appliance ON state is correctly classified, f_p is false positives, which is the number of times an appliance OFF state is wrongly classified as ON, and f_n is false negatives, which is the number of times an appliance ON state is wrongly classified as OFF.

In order to demonstrate the burdensome task of disaggregating the similar loads, particularly with low average power consumption i.e. fridge and freezer, a simple scenario is provided. In this case, the disaggregation practice is applied to the total signal of these two devices using their constructed load models. The outcomes of this scenario is shown in Table 1. As a result, the problem of similar load recognition can be easily realized even in a simple case especially, considering the accuracy rate of FHMM. In fact, this scenario can evidence the recognition difficulties of these appliances in the presence of other loads, regarding the utilization of actual aggregated signal. However, other methods are able to provide a satisfactory accuracy of more than 90%. The RNN is able to prepare a successful training, because of sufficient data of these two periodic appliances in different combination. The exceptional preciseness of FHSMM can be due to the fact that it is able to capture the behavior of time-duration operation of fridge and freezer, which pose a periodic pattern. Consequently, it notably increases the efficiency.

Moreover, the recognition accuracy of five targeted appliances of ECO house 2 is presented in Table 2. Although the training phase of RNN is time consuming, it performs the disaggregation procedure faster in comparison with FHSMM. It can be seen that FHSMM surpasses other methods in appliance-level load recognition and its accuracy falls under 80% only for the kettle. FHSMM and RNN are able to capture the operation sequence of fridge and freezer. However, FHMM completely fails in providing any results for the fridge, which demonstrates its incapability to realize any sequence. In fact, the fridge and freezer have average power consumption values of 75W and 55W with high transients between 800W to 1kW, respectively. Such large variance can cause their operation events to be easily mistaken for each other. In this case, it is difficult to address this issue either by a transient analysis due to the low frequency scenario, or a high-order filtering due to the events loss of other loads. Nonetheless, FHSMM that can infer the operation duration and RNN that can learn the combinations, are able to recognize this challenging situation. Actually, the analysis of such combination of periodic loads with similar low-rate power values has been neglected. Only Parson [23] has aimed to investigate the recognition of fridge and freezer. However, his analysis has intended an energy efficiency practice with no report of disaggregation results. He has utilized the FHMM of only these two appliances in a scenario that the first load is extracted from the aggregated signal and the process disaggregates the second load from the reaming signal [25]. Moreover, the RNN has failed in recognizing the kettle. The reason can be because of the fact that the kettle is a regular load that has not been used every day and thus; it requires more data for training. Furthermore, the kettle frequently poses high variations of power consumption during its short time operations that transform its pattern in combination with other loads. It can be deduced that an effective model of operation cycle of household appliances, enabled by HSMM can significantly enhance the appliance-level load modeling performance [26].

In our case, a dataset of load signatures has been utilized to provide effective load models. However, it can bring about other concerns related to the essence of employed methods. In fact, an important issue with these generative algorithms is that they can lose the generalization. Therefore, they advertise specific cases due to the model parameters, estimated through the tuning procedure with specific prior knowledge. This issue becomes critical with DNN as it can influence the network structure by necessitating the practice of different architectures to realize an accurate structure regarding the case study. This,

TABLE I
THE RECOGNITION ACCURACY OF FRIDGE AND FREEZER USING F1-SCORE IN A SCENARIO OF ONLY TWO APPLIANCES

Appliance	FHSMM	FHMM	RNN
Fridge	99.1%	82.8%	91.5%
Freezer	99.2%	86.9%	93.1%

TABLE II
THE RECOGNITION ACCURACY OF TARGETED LOADS OF ECO HOUSE 2 USING F1-SCORE

Appliance	FHSMM	FHMM	RNN
Fridge	88.7%	0.0%	70.1%
Freezer	90.9%	70.5%	70.3%
HTPC	94.9%	34.4%	74%
Dishwasher	91.7%	76.6%	80.9%
Kettle	76.7%	27.9%	0.0%

in turn, increases human intervention as a pivotal concern of household load modeling approaches. However, DNN are able to provide competitive results with other methods specifically, HSMM. In fact, in order to provide a fair comparison under the same condition, a RNN has been chosen that its nature is consistent with first-order Markovian assumptions [10]. However, RNN can be designated with long memories to consider long-term dependencies for better achievements. Additionally, with further improvement of special designed cores for exceptional DL efficiency, training of large DNN can be possible. As a result, DNN have a great potential for advancement in the future from the perspective of both hardware as well as operating systems and architectures. Such promising potential can influence their success in many areas. Notwithstanding, the NILM framework needs practical techniques that can overcome its particular obstacles. NILM requires a method that can handle the issues related to the limited available data and construct generic models not restricted by individual cases and human intervention. In addition, this method has to avoid complex computations that need heavy operation systems in order to be compatible with smart meter technologies (regarding practical real-time implementations) [27]. Indeed, these particular barriers can still signify the utilization of the efficient variants of HMM as the state-of-the-art approaches.

V. Conclusion

Recent advancements of DNN in terms of optimization algorithms and architectures have promoted their applications in the area of NILM. Therefore, this study provides a realistic comparison between variants of HMM as the state-of-the-art and DL fundamental structures as the cutting-edge approaches of household appliance-level load modeling and recognition. Particularly, FHMM and HSMM as superior variants of HMM and simple RNN as a DL basic model have been analyzed under the same conditions. In addition, the importance of data has been investigated to provide a thorough load modeling procedure. The results have demonstrated that HSMM and RNN are competitive. From a practical perspective, this paper has provided important statements by carefully exploring the essentials of a load modeling practice in the context of NILM. In the future work, the capability of DNN to achieve successful load recognition results in the scenarios with less prior information will be evaluated. Moreover, a combination of both techniques will be studied to provide enhanced designs of appliance-level load modeling process.

References

1 Hosseini, S. S., Agbossou, K., Kelouwani, S., and Cardenas, A., "Non-intrusive load monitoring through home energy management systems: A comprehensive review," *Renew Sustain Energy Rev*, vol. 79, no. April 2016, pp. 1266–1274, 11 2017.

2 Henao, N., Agbossou, K., Kelouwani, S., Dube, Y., and Fournier, M., "Approach in Nonintrusive Type I Load Monitoring Using Subtractive Clustering," *IEEE Trans. Smart Grid*, vol. 8, no. 2, pp. 812–821, 2015.

3 Zoha, A., Gluhak, A., Imran, M., and Rajasegarar, S., "Non-Intrusive Load Monitoring Approaches for Disaggregated Energy Sensing: A Survey," *Sensors*, vol. 12, no. 12, pp. 16838–16866, 2012.

4 Zeifman, M. and Roth, K., "Viterbi algorithm with sparse transitions (VAST) for nonintrusive load monitoring," in *IEEE Symp. Compon. Intell. Appl. Smart Grid (CIASG)*. IEEE, 2011, pp. 1–8.

5 Makonin, S., Popowich, F., Bajic, I. V., Gill, B., and Bartram, L., "Exploiting HMM Sparsity to Perform Online Real-Time Nonintrusive Load Monitoring," *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2575–2585, 2016.

6 Nascimento, P. P. M. d., "Applications of deep learning techniques on NILM," Ph.D. dissertation, Federal University of Rio de Janeiro, 2016.

7 Singhal, V., Maggu, J., and Majumdar, A., "Simultaneous Detection of Multiple Appliances from Smart-meter Measurements via Multi-Label Consistent Deep Dictionary Learning and Deep Transform Learning," *IEEE Transactions on Smart Grid*, vol. 3053, no. c, pp. 1–1, 2018.

8 Kim, J., Le, T.-t.-h., and Kim, H., "Nonintrusive Load Monitoring Based on Advanced Deep Learning and Novel Signature," *Computational Intelligence and Neuroscience*, vol. 2017, no. 10073236, pp. 1–22, 2017.

9 Faustine, A., Mvungi, N. H., Kaijage, S., and Michael, K., "A Survey on Non-Intrusive Load Monitoring Methodies and Techniques for Energy Disaggregation Problem," *CoRR*, vol. abs/1703.0, 2017.

10 Henao, N., Agbossou, K., Kelouwani, S., Hosseini, S., and Fournier, M., "Power Estimation of Multiple Two-State Loads Using A Probabilistic Non-Intrusive Approach," *Energies*, vol. 11, no. 1, p. 88, 1 2018.

11 Dewar, M., Wiggins, C., and Wood, F., "Inference in Hidden Markov Models with Explicit State Duration Distributions," *IEEE Signal Processing Letters*, vol. 19, no. 4, pp. 235–238, 4 2012.

12 Graves, A., "Supervised Sequence Labelling," 2012, pp. 5–13. [Online]. Available: http://link.springer.com/10.1007/978-3-642-24797-2_2

13 Gregor, K., Danihelka, I., Graves, A., Rezende, D. J., and Wierstra, D., "DRAW: A Recurrent Neural Network For Image Generation," 2015. [Online]. Available: http://arxiv.org/abs/1502.04623

14 Elman, J., "Finding structure in time," *Cognitive Science*, vol. 14, no. 2, pp. 179–211, 6 1990.

15 Ghahramani, Z. and Jordan, M. I., "Factorial Hidden Markov Models," *Mach. Learn.*, vol. 29, no. 2-3, pp. 245–273, 1997.

16 Yu, S.-Z., "Hidden semi-Markov models," *Artificial Intelligence*, vol. 174, no. 2, pp. 215–243, 2 2010.

17 Basu, K., Debusschere, V., Bacha, S., Hably, A., Van Delft, D., and Jan Dirven, G., "A generic data driven approach for low sampling load disaggregation," *Sustainable Energy, Grids and Networks*, vol. 9, pp. 118–127, 2017.

18 Beckel, C., Kleiminger, W., Cicchetti, R., Staake, T., and Santini, S., "The ECO data set and the performance of non-intrusive load monitoring algorithms," in *Proc. 1st ACM Conf. Embedded Syst.*, 2014, pp. 80–89.

19 Pöchacker, M., Egarter, D., and Elmenreich, W., "Proficiency of power values for load disaggregation," *IEEE Trans. Instrum. Meas.*, vol. 65, no. 1, pp. 46–55, 2016.

20 Kolter, J. Z. and Johnson, M. J., "REDD : A Public Data Set for Energy Disaggregation Research," *SustKDD workshop*, vol. xxxxx, no. 1, pp. 1–6, 2011.

21 Guzman, C., Rueda, L., Romero, G., Biscans, S., Agbossou, K., and Cardenas, A., "Enabling winter behavior analysis on electrically heated residential buildings by smart sub-metering," *2018 IEEE International Conference on Industrial Technology (ICIT)*, pp. 1213–1218, 2018.

22 Dawei He, Weixuan Lin, Nan Liu, Harley, R. G., and Habetler, T. G., "Incorporating Non-Intrusive Load Monitoring Into Building Level Demand Response," *IEEE Transactions on Smart Grid*, vol. 4, no. 4, pp. 1870–1877, 12 2013.

23 Parson, O., Weal, M., and Rogers, A., "A Scalable Non-intrusive Load Monitoring System for Fridge-Freezer Energy Efficiency Estimation," *NILM Workshop 2014*, pp. 1–4, 2014.

24 "Keras Documentation." [Online]. Available: https://keras.io/

25 Parson, O., Ghosh, S., Weal, M., and Rogers, A., "Non-intrusive load monitoring using prior models of general appliance types," *Proceedings of the 26th AAAI Conference on Artificial Intelligence*, pp. 356–362, 2012.

26 Hosseini, S., Kelouwani, S., Agbossou, K., Cardenas, A., and Henao, N., "A semi-synthetic dataset development tool for household energy consumption analysis," in *IEEE Int. Conf. Ind. Tech. (ICIT)*, 2017, pp. 564–569.

27 Cardenas, A., Agbossou, K., and Guzman, C., "Development of real-time admittance analysis system for residential load monitoring," in *2016 IEEE 25th International Symposium on Industrial Electronics (ISIE)*, vol. 2016-Novem. IEEE, 6 2016, pp. 696–701.

Appendix B - Résumé

B.1 Introduction

La demande d'électricité à l'échelle mondiale est en croissance en raison des processus d'électrification des déférents secteurs de l'économie. En ce qui concerne le secteur résidentiel, la demande d'électricité continue à croître à cause de l'augmentation des surfaces habitables et la substitution des sources d'énergie traditionnelles à savoir le bois, le mazout et le gaz naturel par l'énergie électrique [1]. Dans la province de Québec, la consommation d'électricité par habitant est parmi les plus élevées au monde. Ceci est dû principalement au chauffage de l'espace pendant des hivers relativement froids. Comme illustré dans la Figure B.1, la consommation d'électricité actuelle des bâtiments résidentiels est de 54% et on prévoit une augmentation de 70% d'ici 2050. Cette augmentation nécessite le développement de nouvelles techniques de gestion de la demande et l'adoption plus déterminée des réseaux électriques intelligents. Ces techniques devront aider à anticiper les besoins futurs en électricité et mieux gérer l'équilibre entre la production et la consommation, facilitant ainsi l'intégration des énergies renouvelables et la réduction des besoins en puissance pendant les périodes de pointe [2].

Dans le contexte des réseaux électriques intelligents, les systèmes permettant un suivi en temps réel de la charge électrique des bâtiments résidentiels ont reçu une attention particulière ces dernières années. Ceci se justifie par la consommation accrue d'électricité des appareils électroménagers qui consomment plus de 20% de la consommation totale de la demande mondiale d'électricité. En conséquence, la surveillance détaillée de la consommation par usages a pris une ampleur croissante dans le domaine de la gestion intelligente de l'énergie résidentielle. Ceci à cause de sa capacité de rapporter des informations pertinentes et opportunes permettant aux utilisateurs d'avoir un meilleur contrôle sur leur consommation [6].

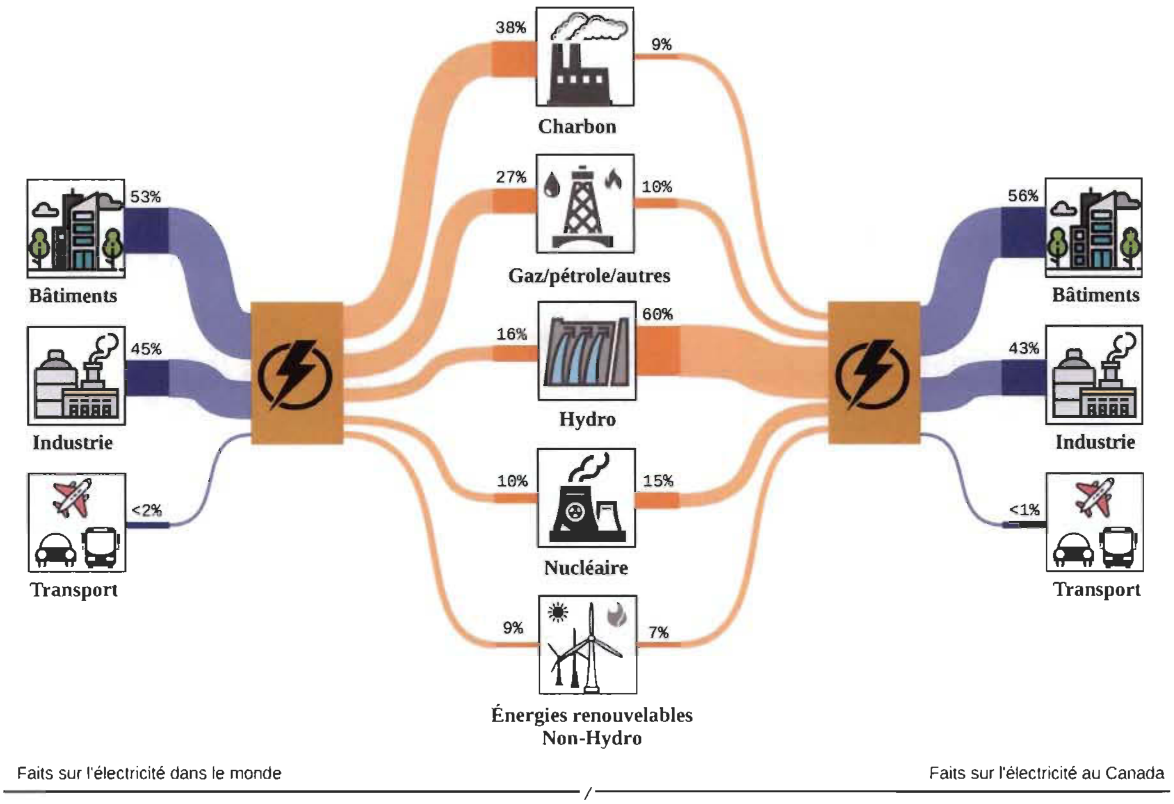


Figure B.1 Production d'électricité dans le monde et au Canada par principales ressources et consommation par principaux secteurs [4], [5].

B.2 Motivation

La surveillance de la charge des appareils électroménagers (en anglais *Appliance Load Monitoring* (ALM)) peut aider les utilisateurs résidentiels à faire des économies non négligeables d'énergie [10]. Le rôle principal des systèmes ALM consiste à quantifier la consommation individuelle des différents usages dans un bâtiment. Le déploiement des technologies ALM facilite le développement des nouvelles fonctionnalités telles que le diagnostic de la consommation et l'automatisation des actions ciblant l'efficacité énergétique. La surveillance de la charge est normalement réalisée à l'aide de deux types de techniques, une est intrusive et l'autre est non intrusive [12], [13]. La technique non intrusive permet d'obtenir une consommation individualisée des appareils à partir d'un seul point de mesure, normalement, au niveau du panneau principal de la résidence [8], [11]. Par contre, la technique intrusive prévoit l'installation de capteurs à l'intérieur de la résidence au niveau de chaque appareil à surveiller [16], [17]. Les deux stratégies de surveillance peuvent faciliter le développement de plusieurs applications telles que la régulation de la consommation d'énergie, la détection de la consommation anormale, la surveillance des personnes âgées et la détection des intrusions [30]. Bien que la technologie non intrusive soit préférable à cause de son coût et la facilité d'installation, dans le futur, les systèmes de communication et la technologie de l'Internet des objets, ou IdO (en anglais Internet of Things (IoT)) vont faciliter le développement de charges intelligentes avec des prix compétitifs capables de rapporter leur consommation en temps réel.

B.3 Problématique de thèse

Le déploiement des systèmes ALM cherche à faciliter deux applications importantes dans le domaine de l'énergie résidentielle: le suivi en temps réel de la consommation des usages et le diagnostic de la charge. Pour réaliser une surveillance efficace, il faut d'abord concevoir des algorithmes pour la détection précise des états de charges, qui est l'objet principal des études dans la littérature. Pour cela, une base de données appropriée permettant de stocker les modèles et les signatures des différents appareils doit être construite. En plus, une méthode de détection des anomalies fiable et cohérente avec les modes d'opération des charges est requise. En considérant ces aspects, trois problèmes particuliers sont abordés dans le cadre de cette thèse, à savoir l'intégralité de la base de données, l'apprentissage en ligne de systèmes de surveillance et la détection d'anomalies [11], [31], [32].

B.3.1 Intégralité de la base de données

L'exhaustivité d'une base de données est une condition déterminante dans l'efficacité des approches pour le suivi non intrusif de la consommation des usages résidentiels. En effet, les algorithmes de surveillance nécessitent des informations *a priori* suffisantes afin d'obtenir des résultats fiables pendant la phase de détection ou désagrégation [33], [34]. Une base de données appropriée doit comprendre des informations concernant les caractéristiques électriques telles que la puissance pour chaque mode d'opération. Elle doit aussi considérer les attributs structurant le comportement ou l'évolution temporelle du profil. Toutefois, la collecte d'une telle base de données est une tâche coûteuse en raison de la variété des appareils [35], [36]. Ce problème s'accroît en présence des usages ayant des signatures électriques liées aux conditions géographiques et climatiques. Par exemple au Québec, le chauffage électrique (en anglais Electric Space Heaters (ESH)) et le chauffe-eau électrique (en anglais Electric Water Heaters (EWH)) représentent plus de 70% de la consommation d'électricité en raison du climat froid [25]. Ceci est dû au fait que ces deux appareils sont peu étudiés dans le domaine scientifique, ces appareils énergivores peuvent créer des scénarios complexes pour les techniques conventionnelles de surveillance. En plus, peu de données et modèles considérant les charges électrothermiques propres aux régions froides sont accessibles au public. Ces limitations motivent le développement des outils de simulation capables de générer des données pouvant être utilisées pour le test et la validation des nouvelles méthodes de surveillance considérant les particularités du climat nordique[10], [11].

B.3.2 Apprentissage en ligne de systèmes de surveillance

La viabilité d'un système de surveillance de la charge concerne essentiellement la précision des systèmes non intrusifs (en anglais Non-intrusive Load Monitoring (NILM)) où les coûts sont basés sur le sous-mesurage, en raison de la complexité algorithmique de la surveillance non intrusive qui augmente de façon considérable avec le nombre d'appareils ciblés. Un scénario efficace de surveillance devrait centrer l'analyse sur les charges ayant une demande d'électricité importante. La capacité du système à déterminer avec précision la consommation des différents usages dépend fortement de la qualité de la base de connaissances. C'est-à-dire, de l'ensemble de modèles et de signatures ayant un pouvoir discriminant suffisant pour le processus de reconnaissance. La littérature scientifique du domaine a généralement privilégié la surveillance basée sur des méthodes supervisées en raison de leur précision [17], [23], [24]. Toutefois, la question d'apprentissage pendant le temps d'opération reste une des limitations majeures des approches NILM existantes [19], [36], [43], [44]. En effet, il est difficile de configurer un dispositif NILM pour qu'il puisse opérer dans tous les scénarios et avec toutes les charges d'une résidence. En plus, les charges peuvent avoir des signatures et cycles d'opération non homogènes dans le temps. Cette situation peut entraîner une perte graduelle de précision, car le modèle ou la signature s'éloignent des informations statiques introduites dans la phase d'apprentissage. Il est donc nécessaire d'aborder le problème d'apprentissage en ligne des systèmes NILM dans des conditions dynamiques telles que le changement ou l'installation des nouveaux appareils, l'effet saisonnier, la dégradation d'équipements, entre autres [51].

B.3.3 La détection d'anomalies

La surveillance automatique de la charge peut faciliter le suivi du comportement individualisé des appareils, en particulier, pendant une opération anormale ou un état de défaillance. La détection d'anomalies cherche à améliorer l'efficacité énergétique globale des résidences en facilitant l'intervention des utilisateurs afin de corriger des modes d'opération signifiant des pertes énergétiques considérables [54], [55]. La détection des anomalies est basée sur la surveillance continuelle des profils de consommation à partir des algorithmes capables de détecter les déviations par rapport aux conditions normales. Ces algorithmes peuvent être développés dans le cadre de l'approche intrusive et non intrusive [31], [56]. Toutefois, la précision limitée des méthodes non intrusives empêche d'avoir des résultats concluants dans l'inférence des états anormaux. Ceci à cause de l'incertitude des méthodes de désagrégation qui dépasse celle admise pour les méthodes de détection d'anomalies. En outre, la nature dynamique et stochastique des modes de fonctionnement de charges rend difficile la construction de règles de détection assez générales. C'est pourquoi des données acquises à l'aide des systèmes de sous-mesurage doivent être utilisées dans la construction de modèles statistiques décrivant le comportement normal des charges [32], [36], [52], [57]. Ces données sont de plus en plus accessibles à travers des charges et prises intelligentes. De plus, les techniques pour la construction des bases de données et celles de l'apprentissage en ligne sont exploitables dans la construction des modèles décrivant l'opération normale des charges [58].

B.4 Objectifs et contributions

L'objectif principal de cette thèse consiste à proposer des approches pour la surveillance en ligne et la détection des anomalies des charges résidentielles. Les approches proposées ciblent les charges ayant un impact considérable sur la consommation d'électricité totale d'une résidence. En conséquence, les objectifs spécifiques suivants ont été considérés:

1. Réalisation d'une étude pour établir les conditions clés qui permettent la mise en œuvre des systèmes ALM dédiés aux appareils énergivores. Des analyses démontrant la complexité de la surveillance pour le cas des maisons canadiennes est aussi l'objet de cette étude. Pour répondre a cet objectif en termes de données, un outil pour la génération de séries temporelles semi-synthétiques a été proposé.

2. Développement d'un système pour la construction automatique des modèles des charge résidentielles. Pour cela, un mécanisme capable de gérer les modèles des appareils, de fournir des informations de fonctionnement et de quantification d'énergie a été proposé. La principale motivation du développement de ce mécanisme consiste à doter la technologie ALM d'une capacité de diagnostic. En conséquence, une approche adaptative en ligne de construction de base de données a été proposée pour tenir compte des caractéristiques dynamiques des profils des charges.

3. Proposition d'un algorithme pour la détection des anomalies à partir d'un traitement statistique automatique des données non agrégées des appareils. Cet algorithme cherche à saisir efficacement l'écart entre le fonctionnement normal et celui qui peut présenter des anomalies. Cette approche permet d'utiliser les technologies ALM de manière efficace à des fins de diagnostic en temps réel.

Les contributions principales de cette thèse sont d'ordre méthodologique:

- En raison du manque d'information concernant les charges énergivores canadiennes, une approche de génération de données a été proposée afin de i) développer un outil capable de générer des données synthétiques sur les appareils de chauffage de l'espace et le chauffe-eau; ii) créer des scénarios de surveillance et de contrôle de la charge sur une période prolongée en utilisant l'effet temporel ou calendaire lié au temps d'utilisation de ces appareils.

- Approche pour la construction automatisée de la base de données caractérisant les charges d'une résidence a été développé. Cette stratégie cherche à gérer le comportement variable dans le temps des profils de charges résidentiels. L'approche permet de construire une base de données flexible en utilisant des algorithmes simples qui ne demandent pas beaucoup d'informations préalables. Le système est basé sur des techniques de reconnaissance des formes récurrentes. Il est capable de détecter et de mettre à jours les modèles et les paramètres des charges les plus persistants. Le processus d'apprentissage est adapté pour réaliser une adaptation en ligne de la base de données, et la construction des modèles exploite les données extraites directement du signal agrégé.

- Proposition d'une méthode pour la détection en ligne d'anomalies dans l'opération des charges résidentielles. La méthode comporte un module pour l'analyse du temps de fonctionnement capable de saisir tout écart entre le fonctionnement normal et celui problématique. L'algorithme est alimenté par un nombre réduit de mesures électriques à faible résolution d'échantillonage (très compatible avec les technologies de mesurage actuelles).

B.5 Méthodologie

La méthodologie de cette thèse est décrite en trois phases communes comme montré sur le diagramme de la Figure B.2. Tout d'abord, un examen complet est effectué pour caractériser les opportunités et les défis des études de surveillance et le diagnostic de la charge des appareils (en anglais Appliance Load Monitoring and Diagnosis (ALMD)) dans la littérature. Cet examen permet de préciser les objectifs et leurs nécessités. Ensuite, les méthodes de pointe sont explorées afin de définir des mécanismes utiles concernant les objectifs prescrits. En conséquence, des approches connexes ont été proposées et leurs exigences sont satisfaites sur la base de ces techniques. Troisièmement, les simulations analytiques et l'expérimentation réelle sont utilisées pour examiner les méthodes proposées en utilisant des données du monde réel provenant soit de bases de données publiques ou de mesures en laboratoire. Ensuite, les performances, la simplicité, l'applicabilité et les limites de chaque proposition sont analysées en profondeur et comparées aux recherches pertinentes. Les étapes de la méthodologie sont détaillées ci-dessous en fonction de chaque proposition, décrite dans la section précédente.

- Approche de génération de données: afin de développer un outil pour simuler des scénarios réels, des caractéristiques des bases de données publiques ont étudiées. En conséquence, des données réelles des appareils électroménagers provenant d'une base de données bien connue sont explorées afin de modéliser leurs comportements calendriers de consommation. De plus, des simulateurs énergétiques en bâtiments ont été utilisés pour identifier une structure de simulation appropriée pour générer les données synthétiques des charges ciblées (dans notre cas, ESH et EWH). Ensuite, une méthode de post-traitement a été étudiée pour moduler les données artificielles de ces charges et créer des profils de charges ON/OFF.

- Approche de construction de la base de données des maisons: les mécanismes de désagrégation de la charge des maisons sont analysés en profondeur, car ils constituent la base de la modélisation de la charge des appareils au niveau agrégé. En particulier, les méthodes probabilistes ont été examinées en raison de leur capacité de fournir une interprétation physique du comportement des appareils. Cet examen se concentre sur les méthodes d'apprentissage en ligne non supervisé des charges à états finis. En outre,

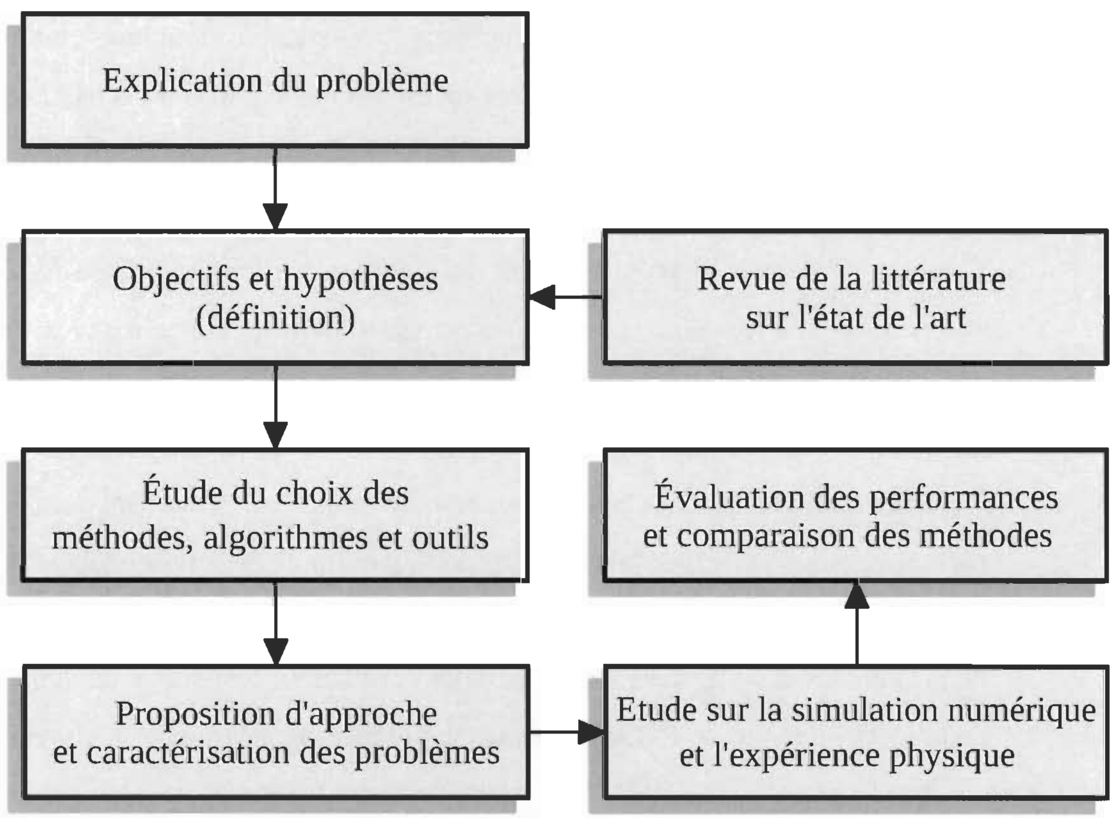


Figure B.2 La méthodologie de recherche

des algorithmes de classification ont été étudiés afin de trouver des techniques efficaces pour classifier le fonctionnement des appareils.

Plus précisément, les méthodes d'agrégation statistiques non paramétriques sont évaluées en raison de leur efficacité dans des cadres non supervisés. De plus, des procédures adaptatives sont évaluées pour déterminer leur capacité à gérer des motifs récurrents et à mettre à jour les modèles pour les charges. Différentes mesures de précision sont analysées afin de définir un ensemble de mesures efficaces pour un examen minutieux des phases de reconnaissance des motifs et de construction des modèles.

- Approche de détection des anomalies en ligne: une recherche approfondie est axée sur les méthodes de détection des anomalies des appareils électroménagers au niveau agrégé. Un aperçu est effectué pour déterminer la nature des anomalies des appareils électroménagers, et leurs caractéristiques électriques disponibles pour une expérimentation réelle. Ainsi, un ensemble d'appareils candidats, situés dans une maison expérimentale de notre laboratoire, sont choisis pour une étude pratique.

  Pour ces appareils, différents scénarios d'anomalies sont utilisés pour analyser leur comportement via une surveillance continue. En outre, des méthodes d'apprentissage automatique sont étudiées pour définir les techniques pratiques adaptées à une mise en œuvre réelle. Cette analyse vise à mettre au point des algorithmes simples pour la modélisation du comportement normal et la détection des opérations anormales. Par la suite, plusieurs tests de diagnostic sont envisagés pour évaluer les performances du mécanisme de détection des anomalies.

B.5.1 Hypothèse de recherche

En ce qui concerne les approches proposées et les méthodes utilisées dans le cadre de cette recherche, les hypothèses suivantes sont prises en compte tant pour la surveillance de la charge ainsi que pour les analyses sur la détection d'anomalies.

- Un système d'acquisition permettant l'échantillonnage des grandeurs électriques en régime permanent et à basse fréquence est considéré. En effet, des mesures de la puissance active à une fréquence d'échantillonnage inférieure à un hertz sont requises afin de faciliter la détection des changements d'état des appareils.

- Les usages ciblés correspondent à des charges ayant une utilisation périodique ou régulière. Leur profil de puissance doit être caractérisé par un nombre fini d'états; c'est-à-dire qu'ils opèrent dans des modes de fonctionnement discrets à cause des contrôleurs thermostatiques embarqués. Ce type de charges est très courant au Québec, et inclut les réfrigérateurs, les cuisinières, le chauffage à convecteurs et le chauffe-eau. Tous ces appareils présentent une demande en énergie élevée et leur surveillance est donc importante pour améliorer les systèmes de gestion et les algorithmes de prévision.
- Les appareils à faible demande ou avec utilisation peu récurrente ne sont pas considérés dans ce projet de recherche.

B.6 Description des résultats publiés

B.6.1 Introduction

Une description générale des publications réalisées dans le cadre de cette thèse est présentée dans cette section. Pour chaque publication, nous détaillons les contributions, l'approche proposée et la technique adoptée de chaque sujet étudié. De la même façon, nous décrivons les aspects importants des formulations mathématiques et les procédures expérimentales permettant de valider les propositions. Par la suite, les résultats sont présentés et discutés afin de montrer l'efficacité des méthodes développées.

B.6.2 Approches pour la génération de données

B.6.2.1 Contexte

La conception et validation des approches de surveillance nécessite des bases de données accessibles à la communauté scientifique. Ces bases doivent considérer les charges propres aux régions présentant des conditions climatiques particulières aux pays nordiques comme le Canada. Dans cette région, les usages énergivores sont constitués par des charges électrothermiques peu étudiées dans la littérature. En conséquent, cet article propose un processus pour la génération des données basée sur des modèles probabilistes. Dans ce cas, le comportement des profils thermostatiques est dépendant des variables climatiques telles que la température extérieure. Un conditionnement par rapport au temps calendaire est aussi considéré afin de répliquer la dépendance temporelle des cycles d'opération des différentes charges de la résidence.

B.6.2.2 Méthodes

Les travaux de recherche aboutissant à cette approche ont été développés en deux phases. Dans un premier temps, une étude exhaustive sur les caractéristiques des bases de données accessibles au public a été réalisée. Ensuite, un outil de génération de données semi-synthétiques avec la structure de simulation ont été schématisés dans la Figure B.3. Les techniques et les modules du simulateur utilisés pour le développement de cet outil sont détaillés ci-dessous.

- Pour le cas des charges conventionnelles, des distributions de probabilité non paramétriques décrivant les cycles d'opération sont construites à l'aide d'un estimateur par noyau de densité du type circulaire (en anglais Circular Kernel Density Estimation (CKDE)). L'estimateur traite les données provenant d'une base de données publique. Le mécanisme de modélisation produit des distributions sur l'état d'opération des charges conditionnées par rapport à l'heure de la journée et au jour de la semaine.
- Le nombre de démarrages de chaque appareil est échantillonné en considérant le nombre d'occupants de la résidence simulée.
- Les profils de puissance des charges sont construits à partir des modèles probabilistes et des signatures de puissance active réelle de la base de données publique.
- Pour construire la géométrie et établir les caractéristiques thermiques du bâtiment, nous utilisons le logiciel (en anglais Building Energy Optimization Tool (BEopt)). Les résidences sont modélisées à partir de deux zones thermiques principales. Cette phase de modélisation tient compte des interactions thermiques, des données climatiques réelles et des données de consommation d'eau chaude provenant du comportement des occupants.

- Pour générer les séries temporelles comprenant la signature thermique de la résidence, le logiciel EnergyPlus est utilisé. Ceci permet de simuler l'architecture ciblée et de fournir les résultats en termes de consommation totale d'énergie, de demande du système de chauffage et le consommation totale d'eau chaude.

- Finalement, une phase de post-traitement permet de générer les profils thermostatiques de puissance pour les charges électrothermiques. L'objectif de ce processus consiste à transformer le profil énergétique générée par EnergyPlus dans un profil thermostatique de puissance. En effet, le simulateur fournit des données de consommation à des intervalles de quelques minutes, qui sont des données continues qui ne reflètent pas le comportement d'un thermostat utilisé pour la régulation thermique. Le résultat est donc un nouveau profil de puissance répondant aux besoin énergétiques imposés par le simulateur.

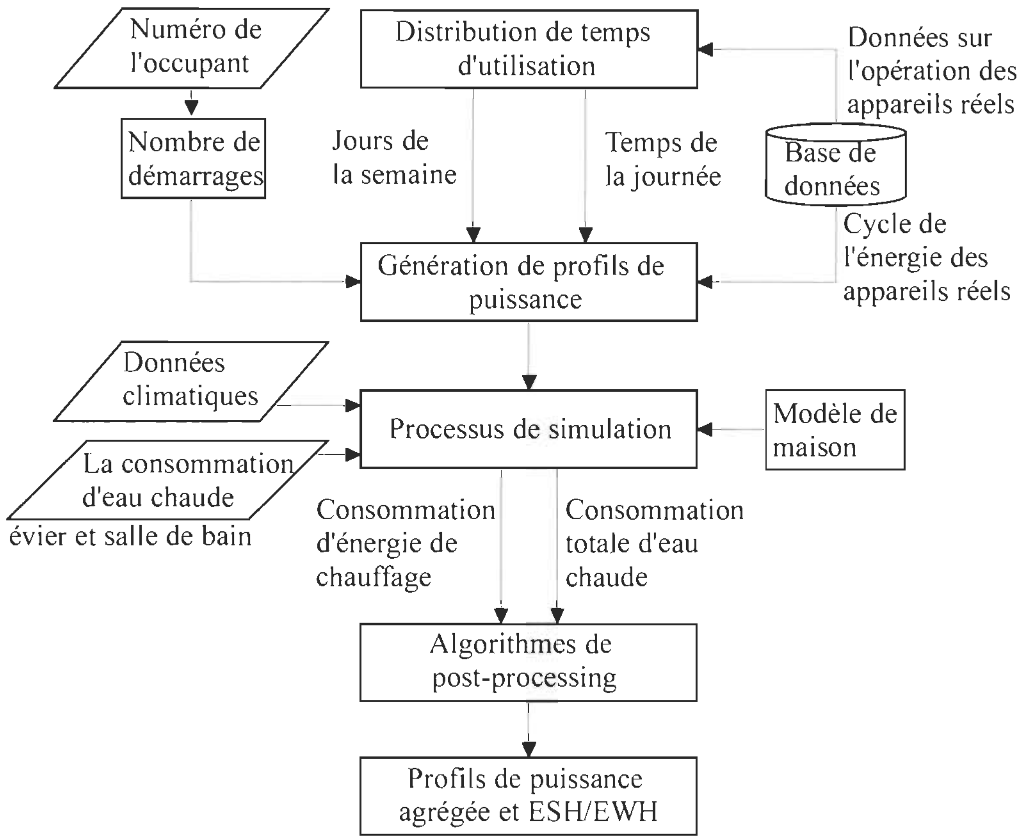
B.6.2.3 Résultats

L'analyse de charges des résidences québécoises ainsi que l'approche de la génération synthétiques des données ont abouti aux résultats suivants :

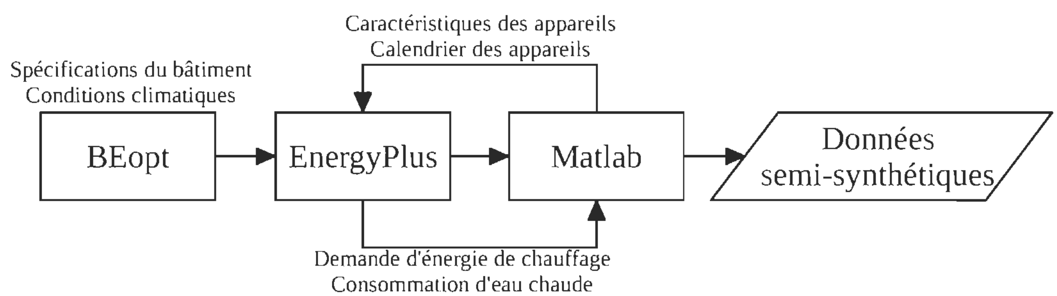
- Détermination des conditions nécessaires pour la conception d'une base de données appropriée pour les études sur la surveillance de la charge.

- Création des profils de puissance plus réalistes des charges thermostatiques telles que l'ESH et l'EWH. Ces profils sont générés en considérant les effets des variables météorologiques. Cette particularité permet de déployer les analyses sur la surveillance de la charge des résidences ayant une composante importante de consommation associée aux appareils électrothermiques.

- Mise en évidence des défis pour le suivi de la charge dans les ménages québécois en présence de charges ESH et EWH. Pour ce faire, la technique de détection de charge basée sur les modèles de Markov cachés a été utilisée.



(a)



(b)

Figure B.3 Les schémas (a) du générateur de données semi-synthétiques et (b) de sa structure de simulation

B.6.2.4 Discussion

La surveillance de la charge ouvre des possibilités et des applications dans le domaine des réseaux électriques intelligents. À cet égard, les points suivants sont discutés:

- *Charges d'intérêt* : l'analyse doit cibler les appareils électroménagers ayant du potentiel pour aider à la fois à réaliser des économies d'énergie et à fournir des services de gestion de la demande. En fait, les charges de chauffage peuvent avoir une certaine flexibilité exploitable dans les problèmes liés à la gestion de la pointe. Déterminer la façon dont ces appareils sont utilisés peut aider à maximiser leur potentiel en gardant le confort des occupants.

- *Applications avancées* : L'intégration des sources renouvelables sera un aspect important des réseaux électriques futurs. En conséquence, la surveillance et la prévision de la charge vont contribuer à une gestion plus efficace de ces ressources. À travers le suivi précis des profils de consommation, les systèmes de gestion d'énergie pourront mieux déterminer l'utilisation de l'énergie produite.

- *Génération de données synthétiques* : L'efficacité des méthodes pour la surveillance dépend de la qualité des données utilisées dans les phases de conception et les tests. Les approches appliquées dans les pays nordiques comme la région de Québec pourront être analysées à partir des mécanismes de simulation avant leurs déploiements.

B.6.3 Construction en ligne de la base de données

B.6.3.1 Contexte

Cette partie du projet vise au développement d'un mécanisme permettant de construire de façon automatique les modèles des charges ayant une utilisation récurrente. Le mécanisme construit et met à jour une base de données flexible à partir des algorithmes statistiques et du traitement automatique des données. L'architecture algorithmique utilisée intègre un système pour la détection de nouveaux événements produits par le changement d'état des charges.

B.6.3.2 Méthodes

Les techniques utilisées permettent de découvrir les modèles et estimer leurs paramètres à partir d'un signal agrégé comme seule source d'information. À cet égard, les modèles de charge découverts sont traités comme des appareils virtuels (en anglais Virtual Appliances (VA)). Ceci à cause de l'absence des connaissances priori sur les charges associées. Le système est capable de découvrir les profils récurrents et d'étendre la base de données afin de les stocker. Le mécanisme d'apprentissage exécute des règles pour la mise à jour des paramètres des modèles déjà existants en présence de nouvelles données. Les techniques utilisées sont issues de l'apprentissage automatique non supervisé. Ces techniques n'utilisent pas de données étiquetées pour reconnaître et mettre à jour les modèles. La Figure B.4 illustre le flux d'information à travers les différents modules comprenant le système. Ce dernier est composée de deux modules d'analyse principaux : 1) le module pour la détection et la supervision des modèles et 2) le module pour la construction et la révision des modèles.

- *Détection et supervision des modèles* : Ce module exécute une procédure pour la reconnaissance des modèles qui permet de détecter les charges virtuelles plus probables qui n'ont pas été modélisées auparavant et créer de nouvelles entrées dans la base de données. Cette procédure tire profit des méthodes de classification soustractif (en anglais Subtractive Clustering) et d'estimation de la densité du Kernel (en anglais Kernel Desnisty Estimation (KDE)).

- *Construction et révision des modèles* : Ce module introduit des algorithmes à faible complexité permettant de générer les entrées pour les nouveaux VA. Le module permet aussi de vérifier la persistance des VAs enregistrés en retirant ceux qui devient obsolètes (peu utilisés). Le modèle pour chaque VA est un HMM avec paramètres dynamiques qui sont mis à jour à partir d'un entraînement de Viterbi.

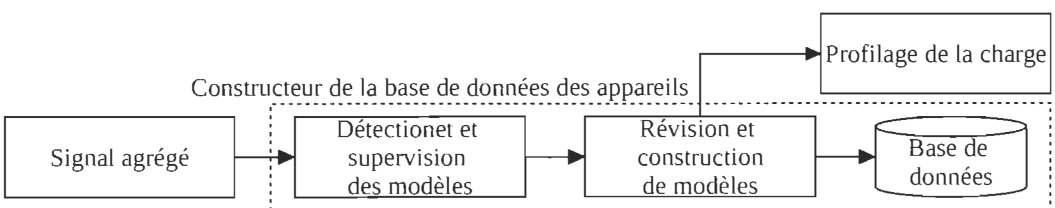


Figure B.4 Diagramme de ADC pour l'approche proposée pour la construction de bases de données.

B.6.3.3 Résultats

Les résultats suivants sont soulignés:

- La méthode est capable de construire des modèles de VA très précis (90% et plus). Ces modèles peuvent être fortement liés aux charges réelles puisque leurs paramètres peuvent expliquer efficacement les caractéristiques électriques d'appareils domestiques inconnus.

- Le système est capable de construire des profils compatibles avec celles des charges réelles. Les profils sont modélisés en deux états avec le processus markoviens. Ces modèles probabilistes permettent d'inférer la séquence d'états d'opération et la consommation d'énergie.

- L'efficacité du mécanisme est également démontrée par l'utilisation des données expérimentales provenant d'un système expérimental.

B.6.3.4 Discussions

Pour l'approche proposée, les points suivants sont discutés

- La structure de modélisation proposée utilise une technique d'apprentissage automatique non supervisée. Cette procédure est capable d'opérer avec peu d'information préalable sur les charges existantes dans la résidence.

- La méthode proposée est basée sur un système de reconnaissance des formes qui n'a pas été utilisée préalablement dans les études de désagrégation de charge.

- La structure que nous proposons utilise une méthode non supervisée, qui nécessite une intervention humaine réduite.

B.6.4 Détection en ligne d'anomalies

B.6.4.1 Contexte

Bien que le suivi de la charge par usage est étudié depuis les années 80. La possibilité d'étudier leur potentiel dans des applications de diagnostic a été peu étudié. Ses nouvelles applications peuvent être considérées comme un élément clé des systèmes de surveillance plus avancés. En conséquence, cette étude a pour objectif la conception d'un système de surveillance avec la capacité de diagnostic.

Les techniques conventionnelles sont conçues pour détecter les charges défectueuses à partir du comportement en puissance. Toutefois, le comportement anormal de ce type de charges se manifeste surtout dans des déviations du temps d'opération. C'est pourquoi cette approche centre les efforts dans la construction des modèles statistiques décrivant le temps d'opération. Les informations sur la consommation d'énergie et de puissance moyenne ont été également utilisées.

B.6.4.2 Méthodes

L'architecture du système pour la détection d'anomalies est illustrée dans la Figure B.5.

- Tout d'abord, les comportements normaux et anormaux des appareils candidats sont étudiés en analysant des facteurs associés à la consommation d'énergie et la demande de puissance dans différents scénarios présentant des anomalies. Le comportement normal est caractérisé par des fonctions de densité de probabilité (en anglais Probability Density Function (PDF)) de ces facteurs.

- Ensuite, une méthode de détection d'anomalie semi-supervisée est développée. Cette méthode utilise des modèles expliquant le comportement normal à partir de lois normales. Les anomalies sont alors déterminées à l'aide de seuils probabilistes estimés avec la fonction inverse cumulative.

- Finalement, une technique en ligne est proposée pour surveiller efficacement la consommation d'énergie et fournir des informations dynamiques pour les algorithmes de détection consécutive d'anomalies. Cette technique détecte les cycles de fonctionnement des appareils et estime leur PDF.

B.6.4.3 Résultats

Une analyse exhaustive sur le comportement anormal des cas d'études à abouti les résultats suivants.

- Un outil statistique permettant de détecter la déviation du comportement normal.

- Un système précis pour la surveillance et la détection des anomalies. Ce système a été évalué en utilisant des bases de données expérimentales. Les performances obtenues à

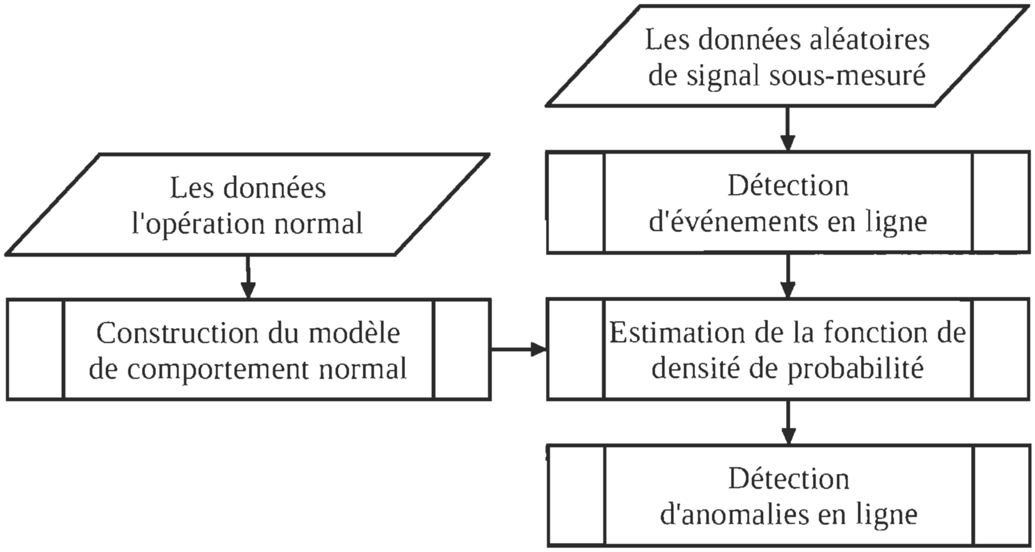


Figure B.5 Diagramme du système de détection en ligne des anomalies au niveau des appareils électroménagers.

partir de l'analyse de plusieurs scénarios démontre la capacité de généralisation et la robustesse de ce mécanisme.

– Une analyse sur la stratégie appropriée pour gérer le temps de détection d'une anomalie en regardant les différences entre le fonctionnement défectueux et celui anormal d'un appareil.

B.6.4.4 Discussion

Une approche de détection en ligne des anomalies des charges résidentielles a été proposée dans le cadre de cette thèse. Le système a été évalué dans un ensemble de scénarios en utilisant des données réelles. Les aspects suivants sont soulevés :

– Capacité de généralisation : Bien que le système proposé soit validé sur un seul type d'appareil, il reste assez général pour l'utiliser sur plusieurs types de charges.

– Test de diagnostic : Notre analyse a utilisé un ensemble de métriques diagnostiques précis pour examiner les résultats.

- Modélisation du comportement normal : Dans notre analyse, un algorithme avec un apprentissage supervisé a été utilisé pour créer un modèle efficace des comportements normaux des appareils candidats.

- Décision de diagnostic : Un système de surveillance de la charge devrait être capable de réaliser un diagnostic rapide. Néanmoins, une décision rapide dans une opération anormale dépend de différents éléments qui demandent des études plus approfondies.

B.7 Conclusion

Cette thèse a porté sur le suivi de la consommation des charges résidentielles. Pour cela, trois questions de recherche ont été abordées, à savoir i) la génération des données, ii) la construction en ligne de la base de données et iii) le diagnostic sur les cycles d'opération anormale. Les approches proposées ont été décrites dans trois publications sous forme d'articles scientifiques.